Lateral motion tracking of automobiles

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Abstract – *Radar sensors, though successful in range parameters tracking, fall short in lateral characteristics tracking. On the other hand, vision systems carry out perfect estimation for lateral motion, but range parameters estimation does not surpass the performance of radar. The exact estimation of vehicle's motion characteristics appears to be a crucial issue in modern automobile collision avoidance systems. Thus, a fusion system comprising of a radar and a FLIR could offer an overall accurate estimation for targets moving in highways. The main scope of the paper is the presentation of a double Kalman based filter which strives in lateral motion estimation mainly. The performance of the filter is tested by means of simulated data sets and compared with the results of the popular fusion method of cross-covariance matrix and the single sensor tracking for each sensor.*

Keywords: Fusion, Infrared, Radar, Kalman, Path prediction, Collision Avoidance.

1 Introduction

Research on next generation Adaptive Cruise Control ACC and Forward Collision Warning (FCW) systems has proved that systems using only one sensor often lack reliability and robustness in specific situations [1]. Meanwhile, the combination of a fusion system consisted of mmw radar and a camera is very common in the literature concerning such systems [2, 3, 4 and 5]. Algorithms implementing that fusion system for automotive applications are a very promising field of research, and towards this direction this paper aims to contribute.

Radars are robust against bad weather, for example rain and fog, they carry out very accurate range and radial velocity estimates, but tracking of lateral motion attribute appears to be an important handicap. This problem is addressed in [2, 6], in automotive real-time systems tracking obstacles and lane information. On the other hand, a vision sensor achieves efficient lateral estimation, but falls short in longitudinal parameters estimation. In Fig. 1, the position measurement errors for the 2 sensors are shown as an example. With the red ellipses the tentative areas of a known radar observation are depicted, those areas derive from the calculations of the used mmw sensor with radial and angular accuracy σ_R = 1m and σ_θ = 0.01 rad respectively. The field of view of the radar is also obvious. For the video sensor these areas are also depicted with the green ellipses.

The camera's position estimation demands initially the process of image processing and afterwards the transition from image to ground plane. The error that is accumulated from the transitions, the image processing and the pitch angle of the camera, inserts uncertainty in longitudinal position mainly. The lateral position is unaffected from pitch and so the error is less and the measurements credible. On the other hand, the lateral estimation of the radar is affected from the angle quality of measurements and as shown in Fig. 1 in great distances the efficiency is falling, and there, the camera estimation can be very useful. These imprecise lateral measurements stem from the fact that cars do not have defined reflection points [1].

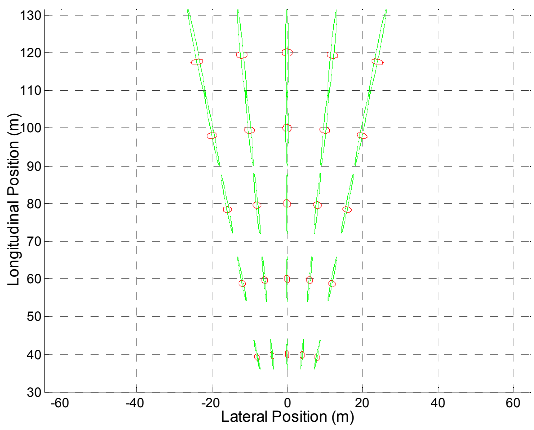

Fig. 1 Camera and radar accuracy.

Thus, a fusion system consisted of a mmw radar and a camera can improve the motion parameters estimation of objects tracked by an automotive application. Data fusion is intuitively recognized as the only promising technique to artificially generate a new powerful sensor, which while combines to the maximum possible extent the individual sensor capabilities, simultaneously strives to eliminate their drawbacks.

A hybrid tracking scheme is presented here, which deploys measurements and tracks in a double filter (DF) technique that compensates the dynamics of moving target tracked by an automotive fusion platform integrated on a vehicle. The existence of the aforementioned 2 sensors is a prerequisite for the proper functionality of the method.

The structure of the paper is as follows: it starts giving the structure of the radar and image tracking systems that allows the implementation of the proposed method. In turn, the fusion methods for the overall system are described. Finally, the results are tested by means of several simulated data sets.

2 Tracking System design

2.1 Radar Tracking System

In this paragraph the main parts of a tracking system will be mentioned in brief. In general, the radar tracking scheme adopted was proposed by [7] tailored for automotive radars and is portrayed in Fig. 2. This figure shows that the Tracking system implemented is separated into the following parts. (1) The data association module that in turn can be split into the individual sub-modules of gating control (equivalently association matrix's creation) and the assignment of each observation to one of the existing tracks. For automotive applications Global Nearest Neighbor (GNN) method for one-to-one observation to track assignment by use of the auction algorithm can be proved adequate. Probabilistic methods like JPDA improve the performance of the system in presence of clutter. Yet, this is counterbalanced by the delay introduced into the overall system from the one-to-N assignment that is demanded. GNN/Auction method is computationally not demanding and sufficient enough, so as to be unnecessary to establish a more robust probabilistic method. (2) The process of track management follows where a track is initialized, confirmed, deleted or simply updated according to an assigned observation (for a GNN system). This can be achieved by means of a simple decision rule that counts the number of hits and misses of each target [8]. And finally (3) the process of filtering and prediction follows where the predicted track values are propagated to the next scan so that the process continues. Kalman filtering is the most common method [9] for this sub-module and is adopted in this paper. What differs in the systems presented in the following sections is the motion modeling (the transition matrix selection). A common constant acceleration matrix is used for the single radar system, a constant velocity model for the vision system, and a most accurate model will be introduced in Sec. 3.2. The individual parts of the tracking system are not independent between each other, but their operations are strongly influenced by each other and many times their operations are interrelated. The one step transition, Markov process equation for the common case is the following [9]:

$$X(k+1) = \Phi X(k) + q(k) + f(k+1|k) \tag{1}$$

$$Y(k) = HX(k) + v(k) \tag{2}$$

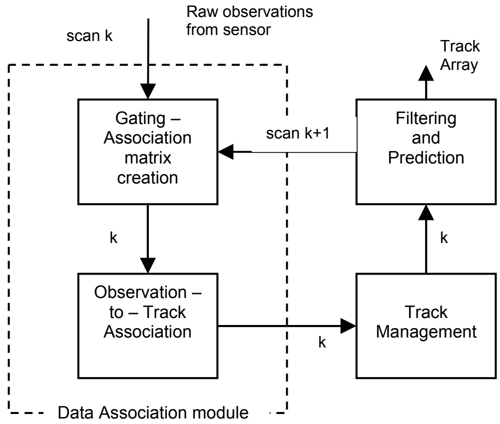

Fig. 2 Tracking System Architecture

Where X is the state vector and Y is the measurement vector. Φ is the transition matrix, $q(k)$ is the zero-mean, white, Gaussian process noise with known covariance Q and $f(k+1|k)$ is the system's input. H is the measurement matrix and $v(k)$ is the zero-mean, white, Gaussian measurement noise with known covariance R. The system can be linear or non-linear, as in the case of IR image processing as it will be shown in Sec. 2.2. The motion model is discrete time-variant with k the number of the scan and T in seconds to be the time step between the scans, which can be constant or varying from scan to scan.

The radar sensor offers reliable measurements for radial parameters (position and velocity), but this does not happen for lateral parameters as the angle measurement is subject to errors. Radial distance (range) can be easily calculated by radar; however the exact position of the target on the 2D plane (angle measurement) is in doubt. The existence of ghost obstacles is also an outcome of these phenomena [1]. In general, angle measurements are small and for values like these it is $\cos\theta \approx 1, \sin\theta \approx \theta$ approximately, thus $x = R\cos\theta$ seems to be reliable while $y = R\sin\theta$ is strongly depended on angle measurements.

In order to implement fusion using cross-covariance with camera data, Cartesian coordinates are selected and a constant acceleration at x and y model is formed. Instead of this, a constant radial acceleration model can be used, with a 3x1 state vector including the radial position, the velocity and the acceleration. The radial approach will be used in the Sec. 3.2; here we show the Cartesian in order to have equivalency with the camera tracker. The transition from Cartesian to polar system and the opposite are made following the next equations.

$$\theta = \tan^{-1}\left(\frac{y}{x}\right) \tag{3}$$

$$R = \sqrt{x^2 + y^2} \tag{4}$$

$$U = \sqrt{U_x^2 + U_y^2} = \sqrt{U_r^2 + U_L^2} \tag{5}$$

$$U_r = U_x \cos\theta + U_y \sin\theta \tag{6}$$

$$U_L = -U_x \sin\theta + U_y \cos\theta \quad (7)$$

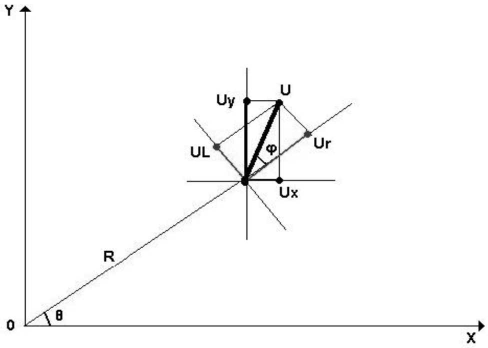

Fig. 3 Cartesian vs. polar coordinate systems

The transition equations for acceleration are equivalent with those of velocity. Taking these into consideration the Cartesian tracking equations are formed.

As measurement is regarded the vector $Y = \begin{bmatrix} x & U_x & y & U_y \end{bmatrix}^T$ and the state vector is: $X = \begin{bmatrix} x & U_x & a_x & y & U_y & a_y \end{bmatrix}^T$. Measurements of u_x, u_y are created using the measurements of range rate (U_r), angle and an estimation of turn rate ($\frac{d\theta}{dt}$) so as $U_L = R\frac{d\theta}{dt}$ to be calculated. A simple *constant acceleration* system can be used with process noise standard deviations σ_{ax}, σ_{ay} (m/s^2) and for measurement noise for position and velocity σ_x, σ_y (m) and σ_{ux}, σ_{uy} (m/s).

2.2 Image Tracking System

The camera tracking system initially demands the transition of processed objects from image to ground plane. The image objects consist of pixel information that by use of a calibration matrix (depended on the camera's characteristics, focal length, skewness factor etc) is transformed into position values. This transformation is a major source of errors as the pitch of camera is "transformed" as backdrop (longitudinal position) uncertainty. All this factors of noise in image objects are taken into consideration at the choice of noise parameters at the simulation process.

IR sensors convey information about the temperature of objects and not typical features of the visible domain. The temperature of the vehicle is mainly concentrated on the wheels, engine and muffler and it is strongly depended on travel time. It is assumed that image processing has been carried out, with its individual steps of identification and merging of image objects.

It is regarderd that infrared camera, after the image processing, extracts the coordinates of image row i and image column j, the object height in row Δi and the object width in column Δj. The centers of the images (i, j) are selected as measurement input for the camera tracker. The measurement vector is $Y = (i \quad j)^T$ and state vector is selected as $X = (x \quad U_x \quad y \quad U_y)^T$. The measurement equation is non-linear, it is:

$$\begin{bmatrix} i \\ j \end{bmatrix} = \begin{bmatrix} \dfrac{a_{11}x + a_{12}y + a_{13}}{a_{31}x + a_{32}y + a_{33}} \\ \dfrac{a_{21}x + a_{22}y + a_{23}}{a_{31}x + a_{32}y + a_{33}} \end{bmatrix} \quad (8)$$

This equation is linearized, with measurement matrix:

$$H(x, y) = \begin{bmatrix} h_{11} & 0 & h_{13} & 0 \\ h_{21} & 0 & h_{23} & 0 \end{bmatrix} \quad (9)$$

$$h_{11} = \frac{a_{11}(a_{31}x + a_{32}y + a_{33}) - a_{31}(a_{11}x + a_{12}y + a_{13})}{(a_{31}x + a_{32}y + a_{33})^2}$$

$$h_{13} = \frac{a_{12}(a_{31}x + a_{32}y + a_{33}) - a_{32}(a_{11}x + a_{12}y + a_{13})}{(a_{31}x + a_{32}y + a_{33})^2}$$

$$h_{21} = \frac{a_{21}(a_{31}x + a_{32}y + a_{33}) - a_{31}(a_{21}x + a_{22}y + a_{23})}{(a_{31}x + a_{32}y + a_{33})^2}$$

$$h_{23} = \frac{a_{22}(a_{31}x + a_{32}y + a_{33}) - a_{32}(a_{21}x + a_{22}y + a_{23})}{(a_{31}x + a_{32}y + a_{33})^2}$$

The parameters a_{nm} are the calibration matrix elements for 2D to 2D, image to ground plane. The calibration procedure is carried out by acquiring images of hot objects at known distances together with the knowledge of intrinsic calibration parameters. These elements have such values that x is mainly depended on i, and y on j. In general, we have as output information of the lateral position (y-coordinate) with great reliability and uncertainty for the longitudinal parameters of the targets, as explained in the introduction.

The Cartesian coordinates' model is used, instead of the polar one, as the latter would portion the x-noise between distance and angle. The linearized measurement vector can update the state vector with a constant velocity at x and y motion model, with σ_{ux}, σ_{uy} the velocity process noise standard deviations in m/s for and σ_x, σ_y the measurement error standard deviations for the 2 axes (m). As it is difficult to generate simulated data for image coordinates, artificial measures of transferred to ground plane image objects are used, in accordance with a linear constant velocity motion model. The non-linear measurement matrix of Eq. (9) can be used on a real-time implementation of the system.

3 Fusion

Initially a fusion system demands a synchronization step of the sensors involved. There are several methods for these modules. One of them is described in [8]. The most crucial issue appears to be the association process between the processed sequences of the 2 sensors. A pure geometric method would not be suitable, as range measurements of FLIR fail due to pitch effect. Thus, a lateral-measurement association seems to be a satisfactory solution. An object to lane assignment for the 2 sensors separately, and afterwards an IR-object to radar-object assignment would follow. As the paper's scope is limited to motion modelling mainly the data association algorithm is omitted from analytical presentation. It should be mentioned that radar objects usually are more than camera objects and so the fusion algorithm is not implemented for the total of radar objects.

A solution for the proposed system could be to implement a sensor-level fusion system by use of cross-covariance [10], but this appears not to strive as longitudinal estimation from IR sensor inserts much noise and outbalance the system's efficiency. The model introduced overcomes this issue taking as measurement the right value from the right sensor, and using the 2 subsystems.

3.1 Fusion by Cross-Covariance method

Firstly, the 6x1 state vectors and the 6x6 covariance matrix of radar estimation are modified so as to be equivalent to camera estimation 4x1 and 4x4, respectively. It is supposed that the acceleration covariance contribution on the other covariance is negligible and therefore it is omitted. The two estimated states $(\hat{x}_R, P_R),(\hat{x}_C, P_C)$ are fused using the cross-covariance, P_{RC}, method [10]. Every point (l,m) of the cross covariance matrix is:

$$P_{RC}(l,m) = \rho[P_R(l,m)P_C(l,m)]^{1/2} \quad (10)$$

with $\rho = 0.4$ for 2D tracking. It is:

$$\hat{x}_f = \hat{x}_R + C[\hat{x}_C - \hat{x}_R] \quad (11)$$

$$C = [P_R - P_{RC}]U_{RC}^{-1} \quad (12)$$

And

$$U_{RC} = P_R + P_C - P_{RC} - P'_{RC} \quad (13)$$

The final fused covariance for $\hat{x}_f$, is

$$P_f = P_R - [P_R - P_{RC}]U_{RC}^{-1}[P_R - P_{RC}]' \quad (14)$$

3.2 Double Filter

The alternative approach is to generate a parallel double filter that will get measurements and tracks from both sensors. As it is mentioned above the radial position and velocity measurements can be taken from the radar sensor but this cannot be done for the angle measurement. On the other hand the y-coordinate measured from the camera is very reliable, but for our model what is needed is an angle measurement.

This measurement can be generated by use of the reliable measurement from the camera and constrainedly the x-coordinate from the radar. Alternatively the calibration matrix from image to ground plane can be fixed so as to derive polar coordinates, but this will worsen the quality of y-measurements. The first method is finally realized so as the measurement of the angle to be:

$$\theta = \tan^{-1}\left(\frac{y_{camera}}{x_{radar}}\right) \quad (15)$$

This "artificial" measurement appears to be the ideal solution as the angle measurement from camera values exclusively fails because of the already mentioned problem of x-estimation by camera. The use of the radar measurement of angle is another solution, in the absence of the IR sensor, but this cannot be proved as better solution. Further down the formulation of the filter depicted in Fig. 4 will be presented. Similar architecture was presented in Section 3.5 of [11] for polar coordinate tracking systems. This paper's approach aims to use this architecture for a fusion algorithm's implementation. The range filter has state vector the radial values and as motion model a constant radial acceleration model. It is $[R \quad U_R \quad a_R]^T$ the state vector and

$$\Phi_R = \begin{bmatrix} 1+\frac{\omega^2 T^2}{2} & T & \mathrm{T}^2/2 \\ \omega^2 T & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \quad (16)$$

is the transition matrix with ω given by the angle filter. $B_R = [\mathrm{T}^2/2 \quad T \quad 1]'$ and covariance matrices are $Q_R = B_R(\sigma_{a_R}^2)B_R{}^T$, $R_R = \begin{bmatrix} \sigma_R^2 & 0 \\ 0 & \sigma_{u_R}^2 \end{bmatrix}$.

The angle filter's state vector is consisted of the angle value and the lateral velocity and acceleration, it is $[\theta \quad U_L \quad a_L]^T$. The transition matrix is

$$\Phi_A = \begin{bmatrix} 1 & \frac{\mathrm{T}}{R}\left(1-\frac{U_R T}{R}\right) & \mathrm{T}^2/2R \\ 0 & 1-\frac{2U_R T}{R} & T \\ 0 & 0 & 1 \end{bmatrix} \quad (17)$$

$B_A = [\mathrm{T}^2/2R \quad T \quad 1]'$, with R and U_R given by the range filter. The covariances are $Q_A = B_A(\sigma_{a_L}^2)B_A{}^T$, $R_A = (\sigma_\theta^2)$. The turn rate value $\omega = \frac{U_L}{R}$ passes to the range filter.

The Eqs. (16, 17) are proved by use of constant $\ddot{R}$ and constant $\ddot{\theta}$ models taking into consideration the following equations:

$$a_R = \frac{d^2 R}{dt^2} - R\left(\frac{d\theta}{dt}\right)^2 \quad (18)$$

$$a_L = \frac{1}{R}\left[\frac{\partial}{\partial t}\left(R^2 \frac{d\theta}{dt}\right)\right] \quad (19)$$

$$u_R = \frac{dR}{dt} \quad (20)$$

$$u_L = R\frac{d\theta}{dt} \quad (21)$$

4 Results from driving simulator

The simulator used targets to approach a car's motion making some assumptions for the data so as to be as realistic as possible. The "true" position extracted by the simulator is subject to Gaussian noise with given standard deviation, in order to approximate the characteristics of the real sensors used. The acceleration and the steering angle that change according to the user's choice are considered as input of the simulator.

The simulator's strength is the fact that the user can handle the values of these two parameters so as the "object" to move on realistic situations of traffic, road environment etc. As the radial parameters are perfectly estimated by radar sensor (and consequently by the range filter of the double filter) the lateral parameters (angle and lateral velocity), are chosen for model verification. The scenarios presented concern vehicles moving ahead of ego-vehicle, which make abrupt maneuvers relatively to ego-vehicle. The ego-vehicle is also moving steadily and the variables depicted are relative in comparison with the ego-vehicle's motion parameters.

From Fig. 5-7 it is obvious enough that double filter surpass the effectiveness of the other methods, which are the single sensor models and the fusion by use of cross-covariance of the 2 track arrays. In every figure each curve is depicted in comparison with the true value, an RMS error for each variable is shown, as well. Radial parameters between single radar processing and double filter are almost similar and very good; the equivalent figures are omitted because of space purposes. In all these figures the "true" values are depicted with blue color, the radar tracking results with red, the camera tracking values with green, fused (cross-covariance) results of the 2 latter with magenta and finally the outcome of the DF technique with the black line.

In Fig. 5 the simulated scenario concerns an abrupt left turn that starts at about scan 60, with impressive results by DF in contrast with the other 3 methods. Fig. 6 has a simple maneuver of an obstacle ahead of ego-vehicle and Fig. 7 has a double maneuver. In both occasions DF succeeds, while other methods fail (mainly in lateral velocity estimation and not so much in angle estimation). What is remarkable is the complete failure of constant acceleration tracking of radar measurements for lateral velocity (red curve in Fig. 5.b, 6.b and 7.b). DF estimation for lateral velocity is not perfect, but it is by far better than the others. Angle estimation from DF is almost ideal (Fig. 5.a, 6.a and 7.a).

5 Conclusion

Theoretically, double filter performs sufficiently, but no simulator can describe a true highway driving instance exactly. This occurs because of unexpected driving situations, continuous variations of driver behavior concerning motion parameters (acceleration and steering wheel angle) for both ego-vehicle and target vehicle, clutter in the environment, sensor failures, excessive pitch for the camera or presence of many reflectors that create "ghosts" for radar, the problem of association between radar and camera objects. Yet, simulation is a significant index for the efficiency of the model The technique of using the best measured quantities from each sensor (range measurements from radar, lateral offset from FLIR) has proved to be fruitful for exact motion parameters estimation. This can be very practical for advanced collision warning systems that use tracking to construct the future path of a vehicle.

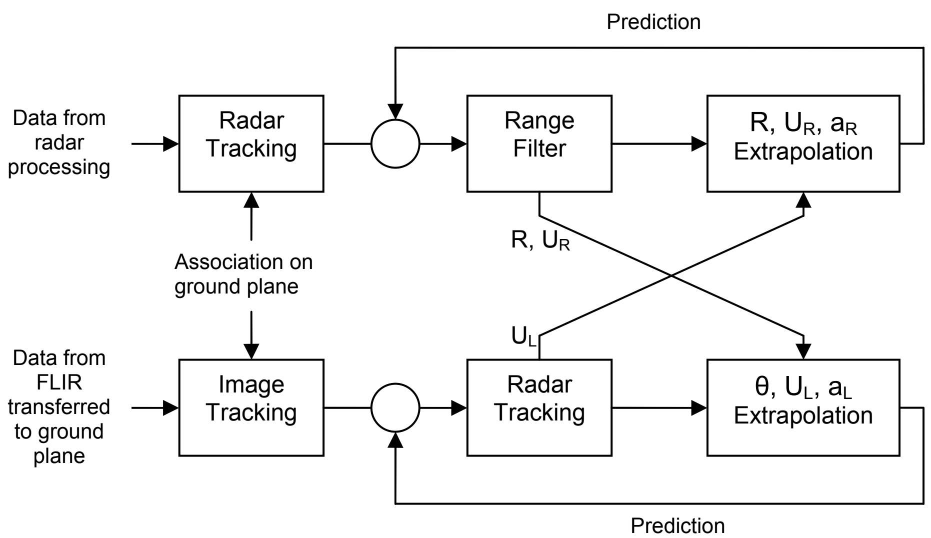

Fig. 4 The Double Filter Block Diagram.

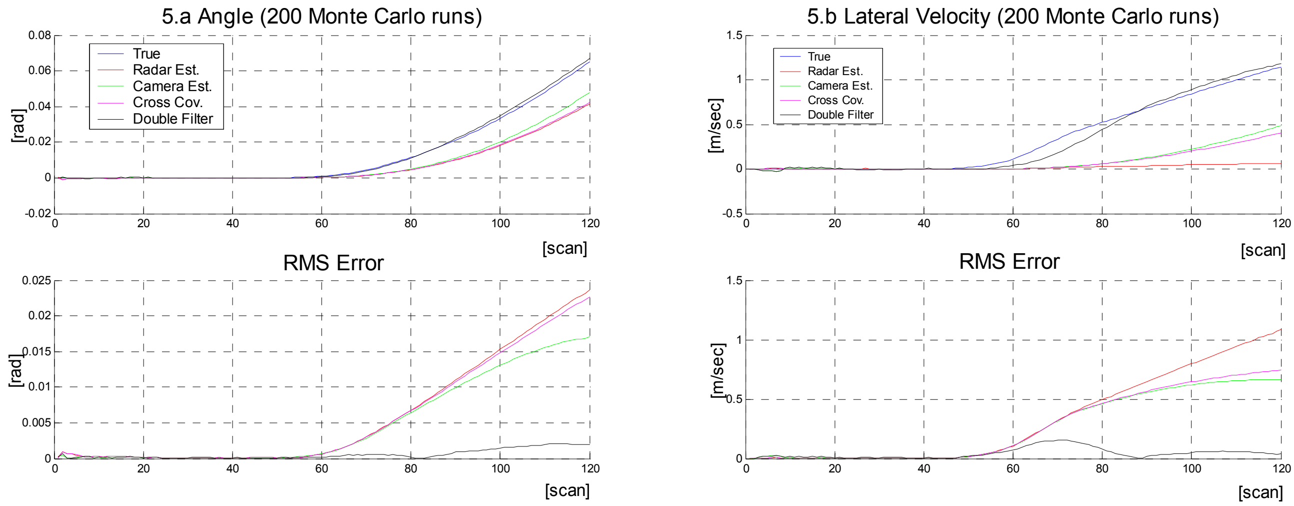

Fig. 5.a-b A turning point.

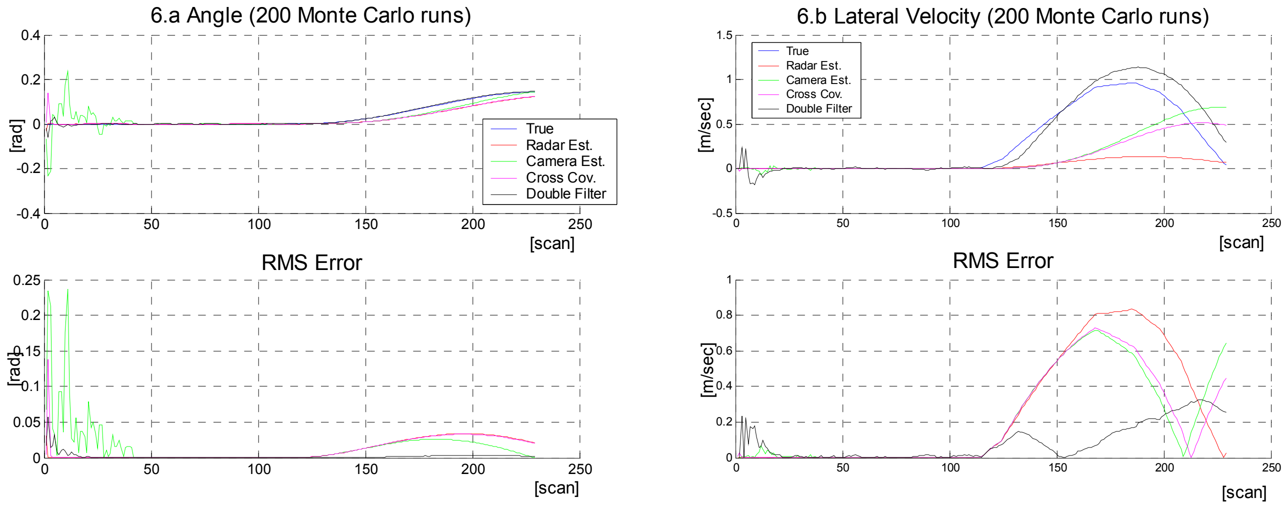

Fig. 6.a-b A simple maneuver.

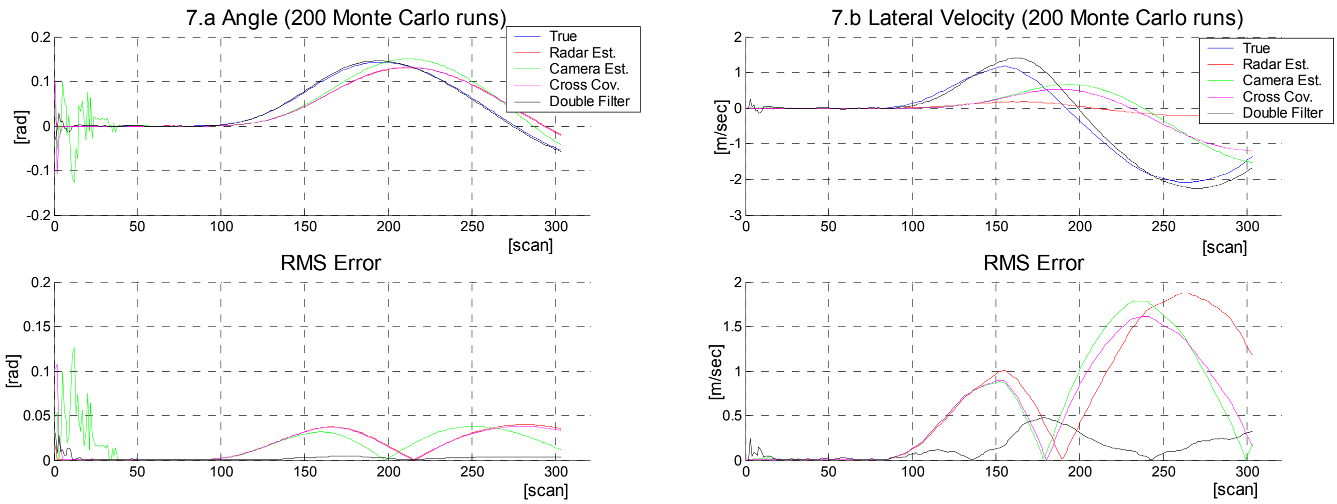

Fig. 7.a-b A double maneuver.

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