Track Heading and Speed Estimation

Dr. Wolfgang Konle

ISEG 46
EADS Germany
Clude-Dornier-Str.
88090 Immenstaad
wolfgang.konle@eads.com

Abstract: A new method to enhance the performance of multi radar tracking systems is presented in this paper. In parallel to an IMM model type tracker a second tracker estimates track heading and speed based upon differential measurements from multiple sensors. A differential measurement contains the differences between two subsequent measurements from one sensor. This new method accepts information from multiple sensors but completely avoids sensor registration problems.
While a common multi radar tracker must take into account at least residual registration errors, the heading/speed tracker accepts the full accuracy of each individual sensor. This leads to high manoeuvre susceptibility and also to a high stability in the non manoeuvre case.
The results demonstrate the tracking performance enhancement achieved by the combination of the new method with the standard tracking method.

1 Introduction

A major problem in tracking of multiple targets with multiple sensors is sensor registration. Even after application of high sophisticated sensor alignment procedures a residual systematic error remains. Taking into account this non Gaussian error, forces to apply more restrictive filters. The side effect of restrictive filters is a reduced tracking reactivity.

A method to avoid the effect of sensor misalignment on the track speed and heading is presented in this paper. Key to overcome the sensor registration problems is the usage of differential information from subsequent measurements instead of absolute values.
The differential azimuth ($d\alpha$) and the horizontal component of the differential range (dr) from all available sensors are used to derive the horizontal speed (v) and the heading (φ) as well as the acceleration (a, dv/dt) and the turn rate (ω, $d\varphi/dt$)

The basic idea is to establish an additional separate tracking filter for the estimation of speed and heading, which is stable and robust in respect to misalignment and highly sensitive to target manoeuvres.

The results presented in the paper show, that the separate speed and heading filter provides higher accuracy of speed and heading values as the operational multi sensor tracking system.

1.1 Combination of Filtering Methods

The track heading/speed filter provides estimation values for horizontal speed, heading, acceleration, and turn rate. This information is not sufficient to solve multi target association problems. Therefore only a combination of both methods leads to a complete tracking system. In the combination, both filters are fed with the same measurements and operate in parallel. As soon as the new filter provides a state vector, it can be mixed with the according values derived by the common filter or even completely replace the common filter's track state components horizontal speed, heading, acceleration or turn rate.

2 The Speed and Heading Filter

The Speed and Heading Filter is a common extended Kalman Filter [1] for the estimation of horizontal speed v, heading φ, acceleration a, and turn rate ω. The measurements comprise the distance difference dr and the azimuth difference dα of two subsequent radar measurements (r_1, α_1), (r_2, α_2).

2.1 System model

The system model comprises simple relaxation and maneuver states and is expressed by the following relations:

$$v(t+dt) = v(t) + a\, dt\, e^{-dt/\tau_1} \tag{1}$$

$$\varphi(t+dt) = \varphi(t) + \omega\, dt\, e^{-dt/\tau_2} \tag{2}$$

The relaxation times τ_1 for the acceleration relaxation and τ_2 for the turn relaxation are different and depend on the maneuver state.
In matrix notation it reads as

$$x_k(-)=\Phi_{k-1}x_{k-1}(+) \tag{3}$$

2.2 Measurement model

The measurement model describes the relation between the measurement vector z=(dr, dα) and the state vector x=(v, φ, a, ω) and is expressed by the function z=h(x).

Figure 2-1 shows the geometrical relation between the state vector (v, φ) and the raw measurement vectors (r_1,α_1), (r_2,α_2).

After some algebraic reformatting we finally get:

$$dr = vdt\cos(\varphi-\alpha_2) - r_1(1-\cos(\alpha_2-\alpha_1)) \quad (4)$$

$$d\alpha = \arcsin(vdt\sin(\varphi-\alpha_1)/r_2) \quad (5)$$

for the relation between (dr, dα) and (v, φ, a, ω).
The relation shows, that the model is complete, which means that the measurement values z can be expressed by a function h(x) with the state variables and given constants.

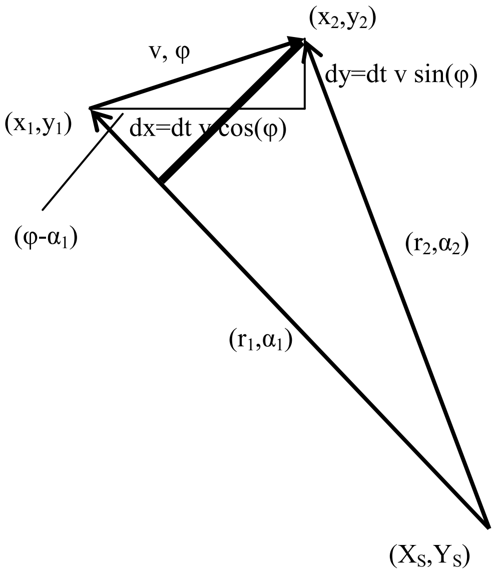

Figure 2-1 Measurement Geometry

2.3 Differential measurement model

The differential measurement model is the Jacobian defined as the partial derivatives of the measurement variables in respect to the system variables: $H_{ij}= \partial h_i/\partial x_j$.
We get:

$$H_{11}: \partial dr/\partial v = dt\cos(\varphi-\alpha_2) \quad (6)$$

$$H_{12}: \partial dr/\partial\varphi = -vdt\sin(\varphi-\alpha_2) \quad (7)$$

$$H_{21}: \partial d\alpha/\partial v = \sin(\varphi-\alpha_1)r_1 dt/r_2^2 \quad (8)$$

$$H_{22}: \partial d\alpha/\partial\varphi = vdt(vdt+r_1\cos(\varphi-\alpha_1))/r_2^2 \quad (9)$$

2.4 Measurement error model

In accordance to the measurement definition, the difference between two subsequent measurements, we get an error covariance matrix R with doubled variance contributions:

$$R = \begin{matrix} 2\sigma_r^2 & \\ & 2\sigma_\alpha^2 \end{matrix}, \qquad (10)$$

2.5 System noise model, manoeuvre detection

The system noise model expresses the variation of the system covariance P due to possible target manoeuvres. Possible target manoeuvres may begin at time t_{k-1} and lead to an increment Q in the system covariance. With this incremental term we get for the error covariance extrapolation:

$$P_k(-)=\Phi^c_{k-1}(P_{k-1}(+)+Q_{k-1})\Phi^{c\,T}_{k-1} \qquad (11)$$

The "c" in the propagation matrix denotes, that the system propagation matrix Φ used in (3) differs from the error propagation matrix Φ^c used in (11).

The system noise matrix Q contains the two components Q_{33} and Q_{44} which express the possible acceleration and turn rate changes. The numerical values are derived from the currently considered measurement triple with the current measurement and the last two additional measurements from the same sensor. The instantaneous adaptation of the system noise to the geometrical shape of a set of observations is very efficient maneuver detection. The opposite, "non maneuver detection," if the acceleration and turn rate is below a threshold, is a not less important criterion to detect maneuver termination or to avoid maneuver initiation upon noise.

2.6 Extended Kalman Filter Definition

With the equations (3..12) the definition of an extended Kalman Filter is complete. The additional equations for the Kalman Gain Matrix (12), the state estimate update (13) and the error covariance update (14) are directly derived from equations (3..12) [1,Table 4.2-1]

$$K_k=P_k(-)H_k^T[\,H_k]P_k(-)H_k^T+R_k]^{-1} \qquad (12)$$

$$x_k(+)=x_k(-)+K_k[z_k-h_k(x_k(-))] \qquad (13)$$

$$P_k(+)=[\,I-K_kH_k]P_k(-)] \qquad (14)$$

The Extended Kalman Filter defined by the equations (1...14) is able to update tracks with subsequent measurements z = (dr, dα). Due to the composite nature of the measurements a problem with the time order arises.

The validity time of a tuple m of measurements $m_1(t_1),m_2(t_2)$ with the measurement values dr,dα is valid at time

$$t_m = (t_1+t_2)/2=(t_1+dt)/2. \qquad (15)$$

The effect of this validity time t_m is that the time stream t_i of measurements $m_i=(t_i,dr_i,d\alpha_i)$ is not monotonous. Nevertheless, the Extended Kalman Filter algorithm requires a processing of the information in a strictly monotonous time order. Let us assume that the slowest radar sensor has a turn time T_{max} and the fastest sensor has a turn time T_{min}. Let us further assume that after one miss of the slowest sensor the resulting measurement tuple with $dt=2T_{max}$ shall be taken into account immediately after a tuple of the fastest sensor has been processed. After processing a tuple of the fastest sensor available at time t_{now}, the minimum time of validity is

$$t_{val/minl} = t_{now} - T_{min}/2. \qquad (16)$$

After processing a measurement tupel with one miss(!) from the slowest sensor, the maximum time of validity is

$$t_{val/max} = t_{now} - T_{max}. \qquad (17)$$

The maximum possible time difference dt_{max} is therefore

$$dt_{max} = t_{val/minl} - t_{val/max} = T_{max} - T_{min}/2. \qquad (18)$$

If as an example T_{max} is 12 seconds and T_{min} is 3 seconds, the validity time becomes rolled back for 10.5 seconds after the reception of the measurement from the slowest turning sensor after one miss. In order to be able to process the incoming information from the slow sensor within the correct time order, the processing since $t_{val/actual}-dt_{max}$ must be repeated with all sets of measurement in the correct time order.
In order to be able to accomplish this, a set of state information back in time with a delay of dt_{max} must be kept in mind for all tracks in combination with all measurement tuples $m_i = (t_{val}, dr, d\alpha)_i$ within the validity time interval I_{time}.

$$I_{time} = t_{val/actual} > t_{vali} > t_{val/actual} - dt_{max} \qquad (19)$$

2.7 Initiation model

Initial values $x(\sim)$ for the system state x based upon one set of measurements z are given by the inverse measurement model function $x(\sim)=h^{-1}(z)$.
But instead of inverting the equations (4,5) it is more easy to derive the inverse measurement model function directly from the geometry. In order to be able to derive the full state vector including a and ω, it is necessary to consider three subsequent measurements of the target position P_0,P_1,P_2.

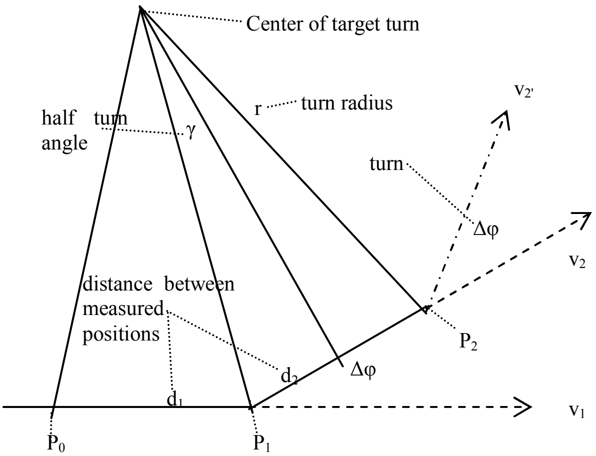

Figure 2-2 Target Movement Geometry

Figure 2-2 shows the geometrical relations based upon three subsequently measured positions $P_0(t_0)$, $P_1(t_1)$, $P_2(t_2)$

We get:

$$v_1((t_0+t_1)/2) = d_1/(t_1-t_0) \tag{15}$$

$$\varphi_1((t_0+t_1)/2) = \arctan((P_1(y)-P_0(y))/(P_1(x)-P_0(x))) \tag{16}$$

$$v_2((t_1+t_2)/2) = d_2/(t_2-t_1) \tag{17}$$

$$\varphi_2((t_1+t_2)/2) = \arctan((P_2(y)-P_1(y))/(P_2(x)-P_1(x))) \tag{18}$$

$$a((t_1+t_2)/2) = \frac{v_2((t_1+t_2)/2)-v_1((t_0+t_1)/2)}{(t_1+t_2)/2 - (t_0+t_1)/2} \tag{19}$$

$$\omega((t_1+t_2)/2) = \frac{\varphi_2((t_1+t_2)/2)- \varphi_1((t_0+t_1)/2)}{(t_1+t_2)/2 - (t_0+t_1)/2} \tag{20}$$

The initial covariance $P(\sim)$ is given by

$$P(\sim)=(P_0^{-1}+(H^TR^{-1}H))^{-1} \tag{21}$$

with a default covariance P_0 which represents default knowledge about possible state values which might be not observable with the available set of measurements. Without the default covariance part, the matrix inversion may lead to non realistic values.

3 Integration of the Heading Speed Filter

Like a common filter, the heading speed filter accepts plots from different sensors for each track and provides an estimate for speed, heading, acceleration, and turn rate. But the results are not suitable to solve multi target association problems. Therefore for multi target tracking this filter only can be used in combination with a common tracking filter which estimates the full state vector including position. The combination of the filters implies that state values of the common tracking filter are modified. These modifications however must be consistent. As an example if the speed estimate becomes modified, the filters capability to estimate acceleration is affected. Therefore the information transfer from the speed/heading filter to the complete tracking filter must comprise the full state vector (v, φ, a, ω). Another aspect is the decision, to which extend the estimate of the complete filter is replaced. A fixed rate of 75% has been selected in the examples which are discussed below.

Figure 3-1shows the result using the speed heading estimate in a tracking system. The white path with speed heading display represents the original tracking result, while the yellow path results in a 75%acceptance of the heading, speed estimate in the tracking system. The result shows a reduction of the track displacement of about 30Figure 3-1b shows the same comparison as shown in Figure3-1a for a noisy part of a straight flight path. The red path corresponds to the original tracking result. The figure shows that there is no significant reaction on the noise, if the heading filter is applied.

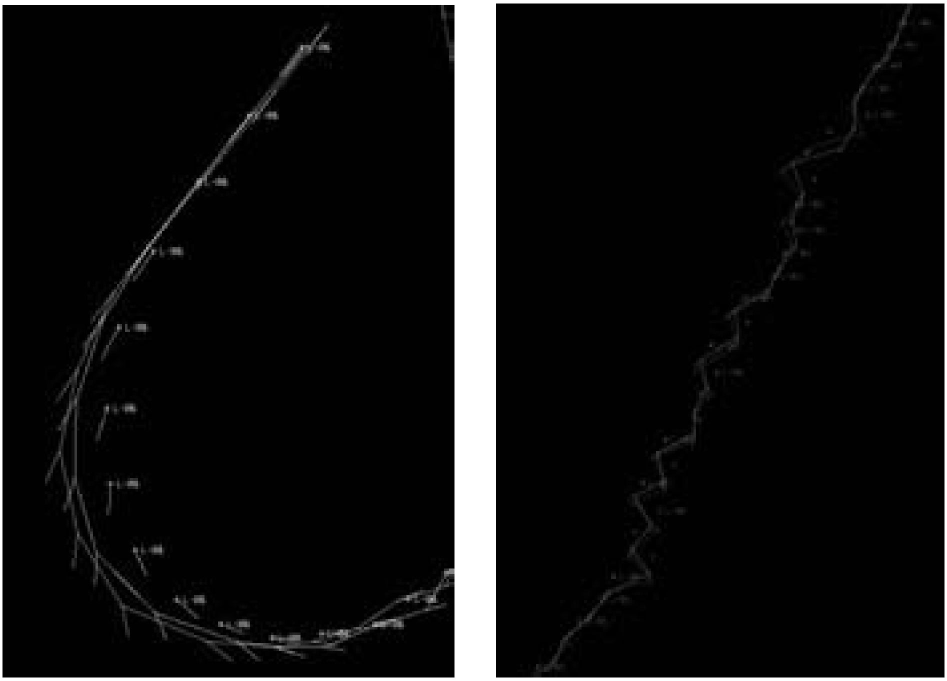

Figure 3-1 a Maneuver and b StraightTracking, one Sensor

4 Conclusion

The solution presented in this paper addresses the problem of multi sensor tracking taking into account sensor registration problems. A standard method to avoid sensor registration problems is to apply single sensor tracking and track fusion. A more stable method is direct sensor data fusion supported by automated and highly accurate sensor registration. But due to still present residual systematic sensor errors a stable tracking requires to underestimate the sensor accuracy. This restriction could be removed with the new method presented in this paper.
A new supplementary multi sensor tracking method using single sensor plot tuples as differential measurements has been presented. The new method estimates speed, heading, acceleration and turn rate of targets. With simulated data, it could be shown that the method is appropriate to generate estimation values which represent the given trajectory values accurately. Applied to tracking with recorded live data, it could be demonstrated that for maneuvering targets the tracking performance can be enhanced significantly, without loss of tracking stability.

Literaturverzeichnis

[1] Arthur Gelb, *Applied optimal estimation*