A new approach to maneuvring target tracking in passive multisensor environment

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***Abstract*—This paper present a new approach to the multisensor Bearing-Only Tracking applications (BOT). Usually, a centralized data fusion scheme which involves a stacked vector of all the sensor measurements is applied using a single estimation filter which copes with the non-linear relation between the states and the measurements. The aforementioned approach is asymptotically optimal but suffers from the computational burden due to the augmented measurement vector and transmission aleas like delays generated by the bottleneck that occurs at the fusion center. Alternatively, since the Cartesian target positions can be determined by fusing at least 2 infrared sensor measurements in 2D case, one can use a local linear filter to estimate the target motion parameters, then a state fusion formula based on the Likelihood of the expected overall local measurements is applied to obtain the global estimate. The simulation results show that the proposed approach performance is equivalent to the centralized fusion schema in terms of tracking accuracy but exhibits the advantages of the decentralized fusion schema like parallel processing architecture and robustness against transmission delays. In addition, the low complexity of the obtained algorithm is well suited for real-time applications.**

I. Introduction

In the lasts decades, passive tracking problems have been addressed in many practical applications, originating from the underwater sonar domain, it rapidly propagates to radar and automotive applications seeking the development of sensor technology. Usually, in such applications researchers focus on the maneuvering character of the target and the non-linearity due to the nature of the measurements. From a survey of (BOT) techniques, the combination of an Interactive Multiple Model (IMM) method and a Kalman Filter based methods like the Extended Kalman Filter (EKF) [7] or the Unscented Kalman Filter (UKF) [3], [8] were successfully implemented. Altoutght, the latter exhibit better accuracy and achieves a good compromise between performance and computational cost. Recently, a multi-mode particle filter was presented in [7] which shows a good performance but requires a high computational capacity. The related methods involves the use of the overall bearing angles measurements in the same time, i.e. the observations are stacked in a single vector, then a non-linear filter which switch between a predefined set of target motion models is applied to estimate the target positions. From the viewpoint of data fusion, a passive bearing-only multi sensor system can be seen as a cooperative data fusion scheme where only the relative angle of the target position can be obtained by a single sensor. Thus, methods that consider a global measurement vector of the overall observations are assimilated to a data fusion process or a centralized fusion scheme. The aforementionned approach is assymptoticaly optimal but have several drawbacks like the high computational burden and transmission aleas due the bottleneck that occurs at the fusion center. Alternatively, in a 2D case, target position can be derived in Cartesian coordinates by combining at least two sensor measurements. Thus, one can use a linear filter such as Kalman filter to estimate local target motion parameters, then applies a decentralized fusion schema which is a weighted combination of the local estimates to obtain the global estimates. Finally, a fusion formula that uses a weighted coefficients which are based on the Likelihood function of the expected local measurements generates the global estimate. This paper is organized as follows: in section 2, the problem formulation and the classical approach are presented for the 2D case. Then a new bearing-only fusion technique which involves a decentralized fusion schema that combines the local Kalman filters with a Singer maneuvring target model [4] is described and the resulting algorithm is presented in section 3. The simulation results comparing the centralized fusion approach are presented in section 4, for an evasive target in passive multisensor environment. Finally, concluding remarks are given in section 5.

II. Problem formulation

In tracking applications, we are interested about estimating the target motion parameters. In case of infrared sensors, the observations are the bearing angles θ_i of the target regarding the sensor positions which are calculated using the following equation:

$$\theta_i = arctan\frac{y-y_i}{x-x_i} + v_i \quad i = 1, ..., M \tag{1}$$

where v_i is a zero mean white noise components, M is the number of sensors and (x_i, y_i) are the correspondent sensor positions as shown in the figure above

The tracking filter is based on a space state representation of the target motion model. From a survey of target models used in maneuvering target tracking applications [2], the Singer

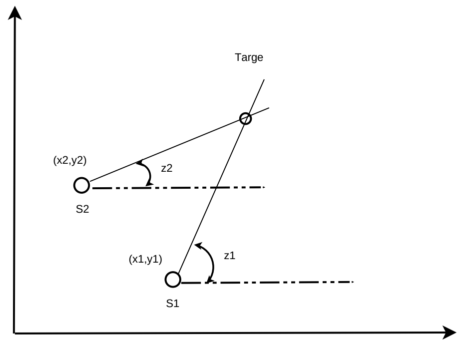

Fig. 1. bearing-only measurement

model is an appropriate compromise between complexity and performance.

A. Target model

The Singer model uses a first order Markov process combined with a zero mean white noise to model the acceleration inputs. Such a process is the state process of a linear time-invariant system given by

$$\dot{a}(t) = -\alpha a(t) + \omega(t) \tag{2}$$

where $\omega(t)$ is a zero mean white noise with constant power spectral density $S_\omega = 2\alpha\sigma^2$. Thus, the autocorrelation of the target acceleration is $R_a(\tau) = E[a(t)a(t+\tau)] = \sigma^2 e^{-\alpha}$ which can be modeled in discrete-time as:

$$a_{k+1} = \beta a_k + \omega_k^a \tag{3}$$

where ω_k^a is a zero-mean white noise sequence with variance $\sigma^2(1-\beta^2)$.

The state space representation of the discrete time Singer model obtained by applying a (sample and hold) filter on the continuous time model is given by:

$$x_{k+1} = F_\alpha x_k + \omega_k \tag{4}$$

where:

$$F_\alpha = \begin{pmatrix} 1 & T & (\alpha T - 1 + e^{-\alpha T})/\alpha^2 \\ 0 & 1 & (1 - e^{-\alpha T}/\alpha \\ 0 & 0 & e^{-\alpha T} \end{pmatrix} \tag{5}$$

and $\alpha = 1/\tau_m$ is the reciprocal of the maneuver time constant τ_m. Thus, it is related to the type of the target. For example for an aircraft, $\tau_m = 60s$ considering a lazy turn and $\tau_m = 10 - 20s$ for an evasive maneuver, as suggested by Signer [4], while σ^2 is the instantaneous variance of the acceleration treated as a random variable.

In [4], the author proposes to model the distribution of acceleration as a *ternary-uniform mixture*, that is the target may accelerate or decelerate with a probability P_1 and moves without accelerating with probability P_0 at a maximum rate of $\pm a_{max}$ with equal probability P_{max}; or accelerate and decelerate at a rate uniformly distributed over $(-a_{max}, a_{max})$. It turn out that:

$$\sigma^2 = \frac{a_{max}^2}{3}(1 + 4P_{max} - P_0) \tag{6}$$

where P_{max}, P_0, a_{max}^2 can be chosen to fit the target motion capability.

To estimate the target position parameters, a non linear-filter is applied. The unscented filter is based on the Unscented Transform denoted (UT) which is a non linear transform that translate a chosen set of representative *sigma* points which capture the posterior mean and covariance of the Gaussian random variables to the third order Taylor series expansion for any non linearity.

B. Unscented Kalman filter

In case of an additive noise the Unscented Kalman filter steps are the following [6]:

1. Assume the following initialization parameters:

$$\begin{aligned} \hat{x}_0 &= E(x_0) \\ \hat{P}_0 &= E((x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T) \end{aligned} \tag{7}$$

2. Calculate sigma points

$$\begin{aligned} \chi_{k-1} = [\hat{x}_{k-1} \;\; & \hat{x}_{k-1} + \sqrt{(n+\lambda)\hat{P}_{k-1}}\hat{x}_{k-1} \\ & -\sqrt{(n+\lambda)\hat{P}_{k-1}}\hat{x}_{k-1}] \end{aligned} \tag{8}$$

using the tunning parameters α,κ,β and $\lambda = \alpha^2((n+\kappa) - n)$. Then compute the weighting coefficients $W_0^m = \lambda/(L+\lambda)$, $W_0^c = \lambda/(L+\lambda) + (1-\alpha^2+\beta)$ and $W_i^m = W_i^c = 1/2(L+\lambda)$ for $i = 1, ..., 2L$ where n, L are respectively the state and the measurement vector dimension.

2.2 Time update:

$$\chi^\star_{k/k-1} = f(\chi_{k-1}) \tag{9}$$

$$\hat{x}_{k/k-1} = \sum_{i=0}^{2n} W_i^{(m)} \chi^\star_{i,k/k-1} \tag{10}$$

$$\begin{aligned} \hat{P}_{k/k-1} = \sum_{i=0}^{2n} W_i^{(c)} & (\chi^\star_{i,k/k-1} - \hat{x}_{k/k-1}) \\ & (\chi^\star_{i,k/k-1} - \hat{x}_{k/k-1})^T + Q_k \end{aligned} \tag{11}$$

$$\begin{aligned} \chi_{k/k-1} = [\hat{x}_{k/k-1}\hat{x}_{k/k-1} & + \sqrt{(n+\lambda)\hat{P}_{k/k-1}}\hat{x}_{k/k-1} \\ & -\sqrt{(n+\lambda)\hat{P}_{k/k-1}}\hat{x}_{k-1}] \end{aligned} \tag{12}$$

$$Z_{k/k-1} = h(\chi_{k/k-1}) \tag{13}$$

$$\hat{z}_{k/k-1} = \sum_{i=0}^{2n} W_i^{(m)} Z_{i,k/k-1} \tag{14}$$

2.3 Measurement update:

$$\begin{aligned} \hat{P}_{zz,k} = \sum_{i=0}^{2n} W_i^{(c)} & (Z_{i,k/k-1} - \hat{z}_{k/k-1}) \\ & (Z_{i,k/k-1} - \hat{z}_{k/k-1})^T + R_k \end{aligned} \tag{15}$$

$$\hat{P}_{xz,k} = \sum_{i=0}^{2n} W_i^{(c)} (\chi_{i,k/k-1} - \hat{x}_{k/k-1})$$
$$(Z_{i,k/k-1} - \hat{z}_{k/k-1})^T \quad (16)$$
$$K_k = \hat{P}_{xz,k} \hat{P}_{zz,k}^{-1} \quad (17)$$
$$\hat{x}_k = \hat{x}_{k/k-1} + K_k (z_k - \hat{z}_{k/k-1}) \quad (18)$$
$$\hat{P}_k = \hat{P}_{k/k-1} - K_k \hat{P}_{zz,k} K_k^T \quad (19)$$

C. Centralized fusion schema

Usually, in passive multi-sensor environment, all the observations are transmitted to a central processor wich implements a non-linear estimation filter that considers a stacked vector of all the received measurements, as shown in the figure 2:

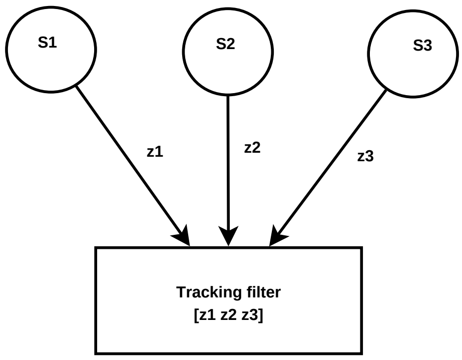

Fig. 2. Centralized fusion scheme

Lets us considers a single maneuvring target observed by M passive sensors:

$$x(k+1) = f_s(x(k)) + Gw(k) \quad (20)$$
$$z_i(k) = h_i(x(k)) + v_i(k), \quad i = 1, ..., M \quad (21)$$

where G is the process noise gain matrix, w is the mode-dependent process noise sequence with zero mean and covariance matrix Q, h_i is a non-linear function that relies between the states and the measurements and v_i is the noise sequence with zero mean and covariance R_i of sensor i.

To estimate the target motion parameters an unscented kalman filter that considers the concatned vector of all the measurement is used as

$$Z = \begin{pmatrix} arctan(\frac{y-y_1}{x-x_1} + v_1) \\ arctan(\frac{y-y_2}{x-x_2} + v_2) \\ . \\ . \\ . \\ arctan(\frac{y-y_M}{x-x_M} + v_M) \end{pmatrix} \quad (22)$$

The most computationally expensive operation in the basic UKF corresponds to calculating the new set of sigma points at each time update. This requires taking a matrix square-root of the state covariance $P_{xx} \in \Re^{n \times n}$. Thus, the resulting Computational Complexity (CC) is $O(n^3)$. But for the centralized UKF, the measurement update step involves the inversion of the measure covariance matrix $P_{zz} \in \Re^{ML \times ML}$. The obtained filter will have a CC of $O((M \times L)^3)$. In addition, while the centralized UKF requires the overall sensors measurements to be available at the same time, any delays that occurs in the transmission system will affect the reliability of the measurements and degrades the tracking performance. To overcome these drawbacks a new approach based on a decentralized fusion schema is adopted.

III. NEW APPROACH

In 2D (BOT) applications, the target position can be derived by combining at least two sensor measurements. The obtained Cartesian position is the result of the intersection of two bearing lines. Let's (x_{ij}, y_{ij}) denote the intersection point coordinates which are obtained by bearing measurement θ_i, θ_j, i.e:

$$x_{ij} = \frac{y_{sj} - y_{si} + x_{sj} tg\hat{\theta}_i - x_{sj} tg\hat{\theta}_j}{tg\hat{\theta}_i - tg\hat{\theta}_j} \quad (23)$$
$$y_{ij} = \frac{y_{sj} tg\hat{\theta}_i - y_{si} tg\hat{\theta}_j + (x_{si} - x_{sj}) tg\hat{\theta}_i tg\hat{\theta}_j}{tg\hat{\theta}_i - tg\hat{\theta}_j} \quad (24)$$

The variance matrix of the new measurements can be directly deduced from (23) and (24). Thus, it is given by the following equation [1]:

$$\begin{pmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 \end{pmatrix} = E\{\begin{pmatrix} dx \\ dy \end{pmatrix} \begin{pmatrix} dx & dy \end{pmatrix}\} = A_{ij} \begin{pmatrix} \sigma_{\theta i}^2 & 0 \\ 0 & \sigma_{\theta j}^2 \end{pmatrix} \quad (25)$$

where

$$A_{ij} = \frac{1}{(tg\hat{\theta}_i - tg\hat{\theta}_j)^2} \begin{pmatrix} (\tilde{x}_{ij} tg\hat{\theta}_j - \tilde{y}_{ij}) sec^2\hat{\theta}_i & (-\tilde{x}_{ij} tg\hat{\theta}_i - \tilde{y}_{ij}) sec^2\hat{\theta}_j \\ (\tilde{x}_{ij} tg\hat{\theta}_j - \tilde{y}_{ij}) \frac{tg\hat{\theta}_j}{cos^2\hat{\theta}_i} & (-\tilde{x}_{ij} tg\hat{\theta}_i - \tilde{y}_{ij} \frac{tg\hat{\theta}_i}{cos^2\hat{\theta}_j}) \end{pmatrix} \quad (26)$$

and

$$\tilde{x}_{ij} = x_{si} - x_{sj}$$
$$\tilde{y}_{ij} = y_{si} - y_{sj} \quad (27)$$

The new measurements exhibit the advantage to have a linear relation with the state vector parameters of the target. So we can write using the new measurement:

$$x(k+1) = f_s(x(k)) + Gw(k) \quad (28)$$
$$z_i(k) = H_i x(k) + v_i(k), \quad i = 1, ..., L \quad (29)$$

Thus, under Gaussian hypothesis, a linear filter as the Kalman Filter (KF) can be implemented to provide a local unbiased optimal state estimate. Then one can combine the obtained local estimates using a state fusion formula that uses weighting coefficients which are the Likelihood of the expected local measurements provided by each KF to obtain the global estimate as shown in figure 3.

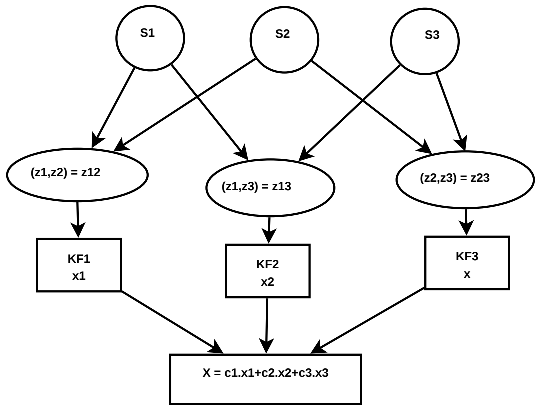

Fig. 3. Proposed approach scheme

Thus, the state fusion formula is given by:

$$\hat{X} = \sum_{i=1}^{L} c_i \hat{x}_i; \tag{30}$$

where c_i are scalars and L is the number of the new Cartesian measurements.
From the unbiased assumption $E(\hat{x}_i) = E(x)$, and taking expectation of both sides of eq.(30), we obtain the normalization condition equation :

$$c_1 + c_2 + ... + c_L = 1 \tag{31}$$

which ensure the unbiasdness of the global estimate.
In the proposed algorithm, a Kalman Filter uses the computed Cartesian position obtained by combining the measurements from two sensor to provide the state estimation of a target motion. Kalman filter is a non biased asymptotically optimal estimation tool for linear systems under Gaussian additive noise assumptions. From [5], assuming a good approximation of the initial target motion parameters x_0 and the initial error covariance P_0 ,the following steps are executed at each time step for each local Kalman filter :
Predicted state and covariance

$$\hat{x}^i_{k/k-1} = F_k \hat{x}^i_{k-1/k-1} \tag{32}$$

$$\hat{P}^i_{k/k-1} = F_k \hat{P}^i_{k/k-1} F_k^T + Q_k \tag{33}$$

Updated measure error covariance

$$\hat{S}_{i,k} = H_{i,k} \hat{P}^i_{k/k-1} H^T_{i,k} + R^i_k \tag{34}$$

kalman Gain

$$K^i_k = \hat{P}^i_{k/k-1} H^T_{i,k} \hat{S}^{-1}_{i,k} \tag{35}$$

Innovation

$$\eta^i_k = z^i_k - H_{i,k} \hat{x}^i_{k/k-1} \tag{36}$$

Filtered state

$$\hat{x}^i_{k/k} = \hat{x}^i_{k/k-1} + K^i_k \eta^i_k \tag{37}$$

Filtered covariance

$$\hat{P}^i_{k/k} = (I_N - K^i_k H_{i,k}) \hat{P}^i_{k/k-1} \tag{38}$$

The obtained local estimate $\hat{x}^i_{k/k}$ is then weighted by a Likelihood function based on the innovation η^i_k and the correpondant measurement covariance error $\hat{S}_{i,k}$ provided by the i^{th} kalman filter. The correspondent unnormalized weighting coefficient is given by:

$$\Lambda_i(k) = \frac{1}{[2\pi^l \|S_i(k)\|]^{1/2}} exp[-\frac{1}{2}\eta^T(k) S_i(k)^{-1} \eta(k)] \tag{39}$$

where l is the measurement vector dimension.
Then a normalization step is applied to the obtained coefficients to ensure the unbiasedness of the global estimate as follows:

$$c_i(k) = \frac{\Lambda_i(k)}{\sum_{i=1}^{L} \Lambda_i(k)} \tag{40}$$

Finally equation (30) is applied to obtain the global estimate. The obtained algorithm exhibits three main advantages, the first one is related to the low level data association process that generates the new measurements which have a linear relation with the state vector parameters. Thus, the use of a linear Kalman filter is allowed leading to reduce the computational complexity of the resulting algorithm. Secondly, from equation (25) we can notice that the variance matrix of each pairs of sensors is updated at each new measurements, this adaptivity is necessary to reduce the effects of the erroneous Cartesian measures obtained using equations (23,24) while the processing of the corresponding error measurement covariance matrix in the Kalman filter steps as shown in eq. (34). The last and not the least advantage is directly drawn from the decentralized fusion architecture which reduce the overall computational burden and exhibits better robustness against transmissions aleas [9].

IV. SIMULATION

In this section the performance of the proposed algorithm is evaluated and compared with the centralized UKF based on a Singer target model. The simulation scenario involves three Infrared sensors which are located at $(0, -3km)$,$(0, 3km)$,$(4km, 0)$. The sampling rate is 1s. The covariances of the measure errors is $\sigma_v = 0.002rad$. The Singer model design parameters are $P_0 = 0.3$, $a_{max} = 50m/s^2$, and $\tau_m = 10s$ which correspond to an evasive maneuvring target. The initial state covariance matrix is $P_0 = diag(10^{-6} \times [400, 100, 10, 400, 100, 10])$.
The flying trajectory is composed from linear segments and turns organized as the following:

1^{th}segment. t=1-24s, Linear flight
2^{th}segment. t=25-37s, turn right with a constant turn rate $w = 0.25rad/s$
3^{th}segment. t=38-61s, a constant acceleration phase
4^{th}segment. t=62-74s, turn left with parameters $w_{max} = -0.25rad/s, \dot{w} = 0.0208rad/s^2$
5^{th}segment. t=75-91s, a constant deceleration phase
6^{th}segment. t=92-104s, turn right with parameters $w_{max} = 0.25rad/s, \dot{w} = 0.0208rad/s^2$
7^{th}segment. t=105-135s, Linear flight

The initial target position is $(2km, 10km)$ with velocity $(-172m/s, 246m/s)$ without acceleration.

Comparison between the tracking performances of the two configurations was made in terms of Root Square Error (RSE) of the position and velocity components of the target motion model using 200 Monte-Carlo runs.

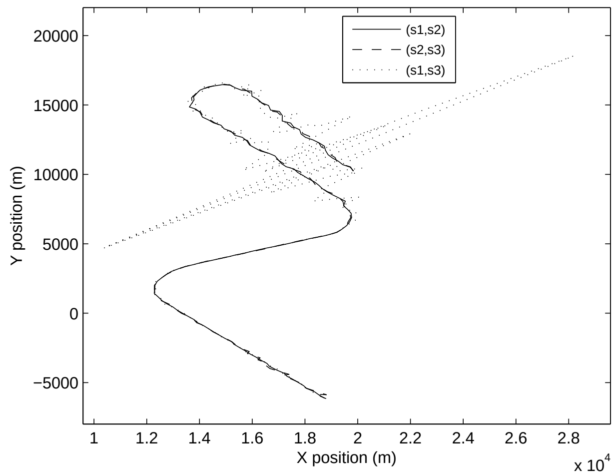

Fig. 4. Computed Cartesian coordinates from sensors pairs

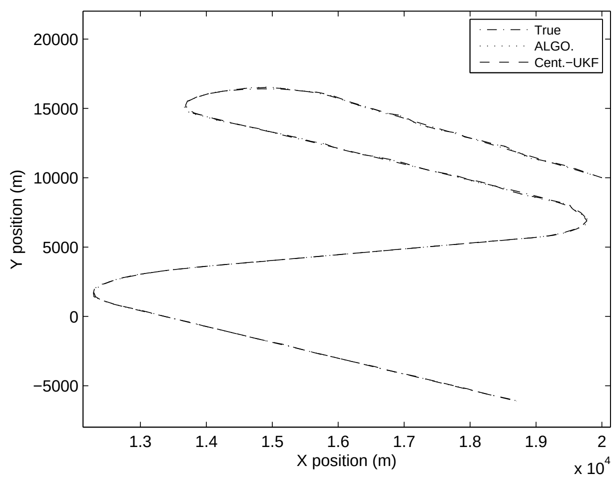

Fig. 5. Target flying trajectory

The Root Mean Square Error (RMSE) of the target position and velocity for the two tested configurations is shown in table.1

	CENT-UKF	ALGO
$x(km)$	0.021	0.024
$y(km)$	0.014	0.016
$v_x(km/s)$	0.017	0.019
$v_y(km/s)$	0.015	0.016

TABLE I
COMPARISON OF RMSE OF CENT-UKF AND ALGO

The computed Cartesian positions for every pairs of sensors is presented in figure 4, while figure 5 shows the real flying

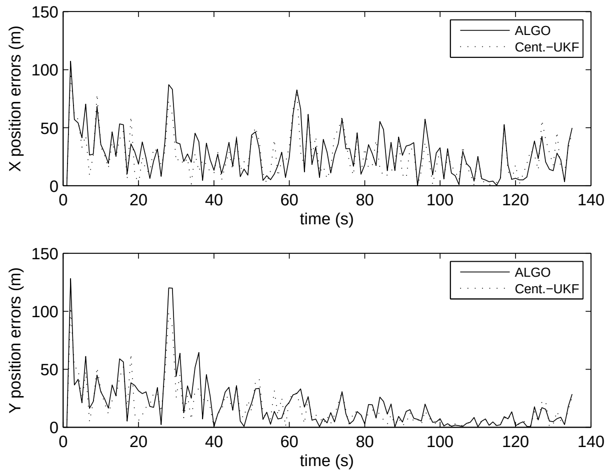

Fig. 6. RSE of Position error estimation in X,Y coordinates

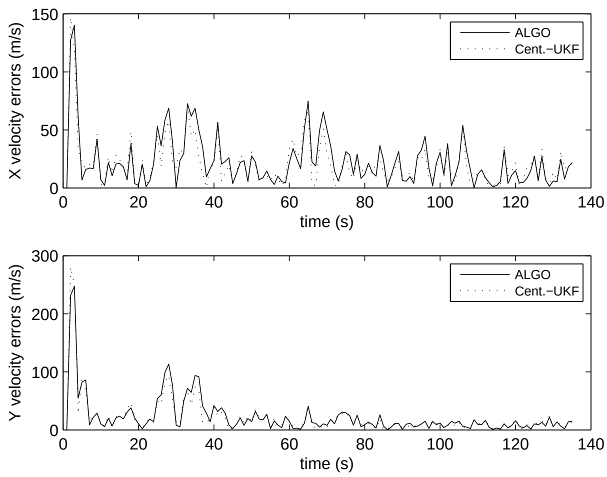

Fig. 7. RSE of velocity estimation in X,Y coordinates

trajectory of the target and the filtered ones using the central UKF and the proposed algorithm. Figures 6. and 7. illustrate the RSE of the position and velocity in Cartesian coordinates. From figure 4. we can notice that the combination of sensors $(s1, s3)$ exhibit a large variance in Cartesian position components compared to pairs $(s1, s2)$ and $(s2, s3)$. Additional simulation scenarios involving the same trajectory but different localization of the sensors shows that the distance between the combined pairs of sensors is inversely proportional to the variance of the obtained Cartesian positions as expected from equation (25). However, the effect of this phenomenon is mitigated during the fusion step, because the weighted coefficient will reduce the correspondent state estimate contribution to the global estimate.

The comparison of the RMSEs reveals that our algorithm has the same performance of the centralized UKF in terms of accuracy. But it exhibits a lower Computational Complexity

(CC) because it is based on local KFs instead of a centralized UKF. CC of KF is $O(n^3)$ while for the Centralized UKF the CC is related to the number of sensors as $O((M \times L)^3)$. Furthermore, the elapsed computational time for our algorithm is reduced because of the distributed processing architecture allowed by the state fusion schema. Thus, the proposed design is more suitable for real-time applications.

In practical applications, the measurements from sensors are not available simultaneously at the fusion center. The transmissions delays due to the distance between the sensors and the transmission protocol which avoids the scratch of the data at the fusion center affect negatively the performance of the centralized fusion schema. Conversely, the decentralized fusion architecture is more robust because it allows a state correction if the corresponding delay is well approximated.

V. Conclusion

In this paper a new approach based on a state information fusion scheme to track a 2D maneuvring target is proposed. The resulting algorithm uses the Cartesian positions of the target obtained by combining at least 2 bearing-only sensor measurements. Thus, a linear filter, namely the Kalman filter, can be used to generate a local state estimate for each pairs of sensors. Then a state fusion process is applied on the overall local estimates weighted by normalized Likelihood coefficients to generate the global estimate. The simulation results show the effectiveness of our approach which can be compared to the centralized UKF in terms of accuracy, while our algorithm exhibits a low computational complexity and better robustness against transmission aleas because of the decentralized architecture that characterizes the state fusion scheme which makes it more suited for real-time applications.

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