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LAINIOTIS FILTERS APPLICATIONS TO SONAR AND RADAR TRACKING: A SURVEY

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ABSTRACT. In this paper, a survey of the applications of the Lainiotis filters to the problems of active and passive tracking is presented. Specifically, the Adaptive Lainiotis Filter as applied to the active and the passive tracking problems is discussed as well as a pseudolinear Lainiotis (partitioning) filter specially developed for passive tracking applications. The performance of the Adaptive Lainiotis Filter, the Extended Kalman Filter and the pseudolinear Lainiotis filter are evaluated via simulation experiments. It is shown that the Lainiotis filters are very successful when used as tracking algorithms, especially when the target is maneuvering, a very realistic situation and one in which the Extended Kalman Filter has been shown to fail.

KEYWORDS. Kalman filters, Lainiotis filters, radar, sonar, nonlinear filtering, parallel processing, adaptive systems.

I. INTRODUCTION

The target tracking problem has been and is still challenging system engineers. In its most general form the problem can be described as follows : Given noisy measurements related to certain target parameters, estimate the target's present position, velocity and course. According to the kind of measurements available, two forms of the problem can be distinguished : active (radar) and passive (sonar) tracking. In radar tracking, the tracker emits a signal - hence actively participates - and measures the time delay between emission and reception of the signal reflected by the target. Thus, a direct (however noisy) measurement of the target position relative to the tracker is available. In sonar tracking, on the other hand, the tracker does not emit any signal; instead it passively observes the target's relative bearing.

The significance of both forms of the tracking problem is well manifested, not only by the extent of the practical applications involving tracking, but by the intensive research efforts devoted to it as well. These research efforts have resulted in a variety of algorithms for solving the active and the passive tracking problems.

In this paper, the Lainiotis filters application to both forms of the tracking problem is presented and comparisons are made with other algorithms found in the literature.

The paper is organized as follows : In section II the active target tracking problem (radar) is described. In section III the passive target tracking problem (sonar) is described. In section IV the Adaptive Lainiotis Filter (ALF) is presented and briefly discussed. In section V the application of the Lainiotis filters to the active and the passive tracking problem is formulated and their performance as active and passive target tracking algorithms is taken up and examined via simulations and also compared to the performance of previously proposed algorithms. Finally, section VI summarizes the conclusions.

II. ACTIVE TARGET TRACKING

The most commonly used model for this type of tracking problem is due to Singer (1970). It is a state space linear model of a possibly maneuvering target, of the form :

$$x(k+1) = \Phi(T,a)x(k) + u(k) \quad (1)$$

$$z(k+1) = Hx(k) + v(k) \quad (2)$$

where x is the state vector consisting of the target position (p), the target speed ($\dot{p}$) and the target acceleration ($\ddot{p}$). It should be noted that p, $\dot{p}$ and $\ddot{p}$ consist of three components in the Cartesian coordinate system. Φ is the transition matrix and is known up to a parameter (a) representing the reciprocal of the maneuver time constant. For example, a is approximately equal to 160 for a lazy term and is approximately equal to 1 for atmospheric turbulence. Φ is also a function of the radar sampling rate (T), usually taken to be small enough (e.g. equal to 0.1). Φ is given as :

$$\Phi(T,a)=\begin{bmatrix} 1 & T & (1/a^2)[-1+aT+e^{-aT}] \\ 0 & 1 & (1/a)[1-e^{-aT}] \\ 0 & 0 & e^{-aT} \end{bmatrix} \quad (3)$$

$u(k)$ is the plant noise sequence (which in this case represents the manual input), which is assumed to be Gaussian, zero mean and to have a variance $Q(k)$ given by :

$$Q(k) = 2a\sigma_m^2 \begin{bmatrix} T^5/20 & T^4/8 & T^3/6 \\ T^4/8 & T^3/3 & T^2/2 \\ T^3/6 & T^2/2 & T \end{bmatrix} \quad (4)$$

where σ_m^2 is again unknown and represents the variance of the target acceleration, which in turn characterizes the type of target we are tracking.

Finally, H is the measurement matrix, given by

$$H = [1 \ 0 \ 0] \quad (5)$$

and $v(k)$ is Gaussian, zero mean white measurement noise with variance σ_R^2. The noise processes $u(k)$ and $v(k)$ are assumed to be uncorrelated to each other and to $x(0)$. $x(0)$ is the system initial state, assumed gaussian distributed with known mean x_o and variance P_o.

Note that if the two unknown parameters (a and σ_m^2) were known, the above linear model would be sufficient. If they are not, one has to augment the state vector by incorporating these parameters. This will result in the following nonlinear model :

$$x_a(k+1) = \Phi_a(T,x_a(k)) + u_a(k) \quad (6)$$

$$z(k+1) = h_a x_a(k) + v(k) \quad (7)$$

where
$x_a(k) = [p(k)\ p(k)\ p(k)\ a(k)\ \sigma_m(k)]^T$,

$\Phi_a(T,x_a(k))$ is

$$\begin{bmatrix} p(k)+p(k)T+p(k)(-1+a(k)T+ \\ e^{-a(k)T})/a^2(k) \\ p(k)+p(k)(1-e^{-a(k)T})/a(k) \\ p(k)e^{-a(k)T} \\ a(k) \\ \sigma_m^2 \end{bmatrix}$$

$q_a(k)$ (the variance of $\{u_a\}$) is

$$\begin{bmatrix} Q(k) & | & & 0 \\ \hline & | & q_{a} & 0 \\ 0 & | & 0 & q_{am} \end{bmatrix}$$

and $h_a = [1\ 0\ 0\ 0\ 0]$.

III. PASSIVE TARGET TRACKING

Contrary to the active target tracking problem, in this case we are only interested in estimating the position and the velocity of the target. In Cartesian coordinates, the equations of motion yield the following state and measurement equations :

$$X(k+1) = X(k) + v_x T \tag{8}$$

$$Y(k+1) = Y(k) + v_y T \tag{9}$$

$$v_x(k+1) = v_x(k) \tag{10}$$

$$v_y(k+1) = v_y(k) \tag{11}$$

$$\beta(k) = \arctan \frac{Y(k) - Y_o(k)}{X(k) - X_o(k)} + e'(k) \tag{12}$$

where $X(k)$ and $Y(k)$ are the two components of the target position at time k, v_x and v_y are the target velocity components (assumed constant in time), $\beta(k)$ is the measured target bearing, $X_o(k)$ and $Y_o(k)$ are the observer position components at time k, T is the sampling interval and $e'(k)$ is a stochastic series of independent and identically distributed r.v.'s, with mean m and variance R. The state vector comprising of X, Y, v_x and v_y is unobservable if the observer is stationary or moves continuously on a straight line (Murphy, 1970). Therefore the observer is assumed to maneuver. Manipulation of eqs. (8)-(12) results in various linearized models (Lindgren and Gong, 1978; Aidala, 1979; Weiss and Moore, 1980; Aidala and Hammel, 1983; Nardone, Lindgren and Gong, 1984). Petridis (1981) formulated the problem in such a way as to estimate $X(0)$, $Y(0)$, v_x and v_y, where $(X(0), Y(0))$ is the initial target position. The required target position can then be computed at any time using these estimates. Petridis' formulation is as follows :

$$x(k+1) = x(k) \tag{13}$$

$$z(k) = h(k)x(k) + \Phi(k,\theta) + e(k) \tag{14}$$

where

$$x(k) = [Y(0)\quad v_y]^T \tag{15}$$

$$\theta = [X(0)\quad v_x]^T \tag{16}$$

$$h(k) = [1\ \ kT] \tag{17}$$

$$\Phi(k,\theta) = [-\tan\beta(k)\ -\ kT\tan\beta(k)]\theta \tag{18}$$

$$e(k) = e'(k)[kTv_x + X(0) - X_o(k)] \tag{19}$$

and

$$E[e(k)] = m[kTv_x + X(0) - X_o(k)] \tag{20}$$

$$\sigma^2_{e(k)} = R[kTv_x + X(0) - X_o(k)]^2 \tag{21}$$

On the other hand, Watanabe (1984) used the following model (Aidala, 1979; Lindgren and Gong, 1978; Aidala and Nardone, 1982) :

$$x(k+1) = \Phi(k+1,k)x(k) - M(k) \tag{22}$$

$$\beta(k+1) = h[x(k+1)] + n(k+1) \tag{23}$$

with $x(k)$ comprising of X, Y, v_x, v_y. $\Phi(k+1,k)$ is a 4x4 matrix given by

$$\Phi(k+1,k) = \left[\begin{array}{cc|cc} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ \hline 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array}\right] \tag{24}$$

where Δt is the sampling interval and $M(k)$ is a four-dimensional vector of deterministic inputs described by :

$$M(k) = \frac{\int t a_s(k\Delta t - t)dt}{\int a_s(k\Delta t - t)dt} \tag{25}$$

where $a_s = [a_{sx}\ a_{sy}]^T$ comprises of the two components of own-sensor acceleration. On the other hand,

$$h[x(k+1)] = \tan^{-1}[x(k+1)/y(k+1)]. \tag{26}$$

The usual assumptions about the nature of the measurement noise are applicable.

IV. THE ADAPTIVE LAINIOTIS FILTER

An extensive presentation of the ALF can be found in (Lainiotis, 1971; 1976). For the sake of completeness, only a brief presentation will be

V. APPLICATION OF THE LAINIOTIS FILTERS TO THE ACTIVE AND THE PASSIVE TARGET TRACKING PROBLEMS

1. Active tracking

The application of the ALF and the EKF to this problem is straightforward. Referring to the models of eqs. (1)-(5) and (6)-(7), an example is presented illustrating how the ALF and the EKF estimate the target state and identify the parameter a. For simplicity, only one Cartesian coordinate is presented, but the results are similar for the others also. For the scenario considered, the target is an aircraft, moving at a velocity of 900 ft/sec, is originally at a distance of 20,000 ft, and suddenly accelerates. The radar data rate is 10 samples per second and the sensor noise is σ_R=200 ft. The average time constant of the maneuver class used in the scenario is 10 seconds (a=0.1).

The ALF was designed with three model conditional linear filters, with the second filter matching the target characteristics. The EKF was designed using the model of eqs. (6)-(7).

Figs. 1-4 depict the position, velocity, acceleration and parameter a per cent normalized estimation errors of the two filters. Fig. 5 depicts the a posteriori pdf's of the three conditional models used by the ALF, while fig. 6 depicts the target acceleration vs time. All results were averaged over 100 Monte Carlo runs.

Studying these figures, we can conclude that the ALF performs far better than the EKF in both estimating the target position and velocity and in identifying the target parameters, even when the target is maneuvering.

2. Passive tracking

The application of the ALF to this problem is not straightforward. Indeed, observe from the model definition equations, that the sample space of the unknown parameters is not naturally discrete. Therefore, some sort of discretization of the parameter space must be performed. Petridis suggests that a two-dimensional area A (within which θ should be) should be defined and that A should be discretized in such a way that the required accuracy be attained. This approach results in a mesh with a relatively high number of nodes. Simulations have revealed that if this procedure is adopted, a large number of observations is required for the algorithm to converge to the correct solution. Therefore, an alternative approach should be considered. Such an alternative approach is to divide A into M nonoverlapping subareas denoted by A_i, (each of dimensions a km x b km/h), i=1,2,...,M, as shown in fig. 7. Over each subarea an independent filter is defined consisting of N Kalman filters and the equations of the ALF. This will be referred to as the "subarea filter". It is not necessary to take N=4 with θ_i, i=1,2,3,4 defined on each node of the subarea; N=2 is sufficient with θ_i, i=1,2 defined on two diagonal nodes. It is clear that there are M subarea filters, each corresponding to a subarea.

Referring to the model of eqs. (13)-(21) three examples are presented. In all examples, the initial observer position is (0,0) and the time interval between observations is T=1.5 min. A was taken to be an area of dimensions (3.6-10 km)x(-12-0.6 km/h) and a=0.8 km, b=1.8 km/h have been assumed.

Example 1: The target is assumed to be initially at point (7,7) (distances in km) and to be moving at a speed of 18.98 km/h, with speed components v_x=-6 km/h and v_y=18 km/h. The observer moves on a straight line course at a speed of v_{ox} = 7.65 km/h, v_{oy} = 10.8 km/h for 10.5 min and then changes course by -135° and travels at a speed of v_{ox}=7.65 km/h and v_{oy}= -7.65 km/h (course -45°), as shown in fig. 8.

Example 2: The target is assumed to be initially at point (10,10) (distances in km) and to be moving at a speed of 20.12 km/h, with speed components v_x=-9 km/h and v_y=-18 km/h. The observer moves on a straight line course at a speed of v_{ox} = 10.8 km/h, v_{oy} = 0 km/h for 10.5 min and then changes course by 90° and travels at a speed of v_{ox}=0 km/h and v_{oy}= 10.8 km/h, as shown in fig. 9.

Example 3: The target is assumed to be initially at point (7,7) (distances in km) and to be moving at a speed of 12.92 km/h, with speed components v_x=4.8 km/h and v_y=-12 km/h. The given here.

Model uncertainty can be summarized by an unknown, finite dimensional parameter vector (parametric uncertainty) or the functional form of the model may be unknown (structural uncertainty).

The discrete adaptive estimation problem under consideration is specified by the following equations :

$$x(k+1) = \Phi(k+1,k;\theta)x(k) + w(k) \qquad (27)$$

$$z(k) = H(k;\theta)x(k) + v(k) \qquad (28)$$

where θ is the unknown parameter, which, if known, would completely specify the model. This parameter is assumed to be a time invariant random variable with known (or assumed) a priori pdf $p(\theta/0) = p(0)$. Furthermore, processes $w(k)$ and $v(k)$ are uncorrelated when conditioned on θ.

Given the measurement set

$$Z_k = \{z(1), z(2), \ldots, z(k)\}$$

the optimal MMSE estimate $\hat{x}(k/k)$ of $x(k)$ is given by

$$\hat{x}(k/k) = \int_{\theta} \hat{x}(k/k;\theta)p(\theta/k)d\theta \qquad (29)$$

where $\hat{x}(k/k;\theta)$ is the θ-dimensional MSE state vector estimate obtained by the corresponding filter matched to the model with parameter value θ and initialized with initial conditions $\hat{x}(0/0;\theta)$ and $P(0,0/\theta)$.

The a posteriori pdf $p(\theta/k)$ of θ, given Z_k, is given by the following recursive Bayes' rule formula :

$$p(\theta/k) = \frac{L(K/k;\theta)}{\int_{\theta} L(k/k;\theta)p(\theta/k-1)d\theta}\, p(\theta/k-1)$$

where

$$L(k/k;\theta) = |P_{\tilde{z}}(k/k-1;\theta)|^{-1/2}$$
$$\exp\{-1/2\|\tilde{z}(k/k-1;\theta)\|^2$$
$$P_{\tilde{z}}^{-1}(k/k-1;\theta)\}$$

with

$$P_{\tilde{z}}(k/k-1;\theta)=H(k;\theta)P(k,0;\theta)H^T(k;\theta)+R(k)$$

$$\tilde{z}(k/k-1;\theta) = z(k)-H(k;\theta)\Phi(k,k-1;\theta)\hat{x}(k-1/k-1;\theta)$$

Comment 1: The above equations pertain to the case that the pdf associated with θ is a continuous function in θ. When this is the case, one is faced with the need for a nondenumerable infinity of filters for the exact realization of the optimal partitioning estimator. The usual approximation performed in this case is to discretize the sample space. There exist, however, cases in which the sample space is naturally discrete. in these cases, the integrals above should be replaced by summations running over all possible discrete values of θ.

Comment 2: It is well known that the adaptive estimation problem constitutes a class of nonlinear estimation problems. Lainiotis' partitioning adaptive algorithm decomposes this nonlinear problem into a linear nonadaptive part consisting of a bank of linear filters, each filter matched to an admissible value of θ and a nonlinear part, consisting of the a posteriori pdf's $p(\theta/k)$, that incorporates the adaptive, learning, or system identifying nature of the adaptive estimator.

Comment 3: An important feature of the partitioned realization of the optimal adaptive estimator is its natural decoupled structure. Indeed, observe that all the linear filters needed to implement the adaptive estimator can be independently realized. This fact enables us to implement these filters in parallel, thus saving enormous computational time.

Comment 4: It is comforting to know that when the true parameter value lies inside the sample space that the adaptive estimator assumes, the estimator converges to this value. This feature has been both analytically proved (Hawkes and Moore, 1976a) and experimentally validated. When the true parameter value is outside the assumed sample space, the estimator converges to that value in the sample space that is closer (in the sense of the Kullback information measure) to the true value (Hawkes and Moore, 1976b).

TABLE I

x(20)=4.0, y(20)=16, x(40)=1, y(40)=25, $E_x|x-\hat{x}|$, $E_y|y-\hat{y}|$

m (°)	σ (°)	K_c	x(0) (km)	y(0) (km)	v_x (km/h)	v_y (km/h)	x(20) (km)	y(20) (km)	E_x(20) (km)	E_y(20) (km)	x(40) (km)	y(40) (km)	E_x(40) (km)	E_y(40) (km)
0	4	16	6.93	7.32	-6.30	[illegible]	[illegible]	15.58	0.22	0.42	0.63	23.34	0.37	1.16
0	6	16	6.93	7.48	-6.30	15.69	3.78	15.33	0.22	0.67	0.63	23.17	0.37	1.83
1	2	14	6.93	7.25	-6.30	17.61	3.78	16.05	0.22	0.05	0.63	24.96	0.37	0.14

TABLE II

x(20)=5.5, y(20)=1, x(40)=1, y(40)=-8.

m (°)	σ (°)	K_c	x(0) (km)	y(0) (km)	v_x (km/h)	v_y (km/h)	x(20) (km)	y(20) (km)	E_x(20) (km)	E_y(20) (km)	x(40) (km)	y(40) (km)	E_x(40) (km)	E_y(40) (km)
0	2	15	10.20	9.72	-9.30	-17.55	5.55	0.95	0.05	0.05	0.90	-7.83	0.10	0.17
0	4	18	10.20	9.52	-9.30	-17.24	5.55	0.90	0.05	0.10	0.90	-7.72	0.10	0.28
0	6	19	10.20	9.35	-9.30	-17.01	5.55	0.85	0.05	0.15	0.90	-7.66	0.10	0.34
2	4	19	10.20	9.41	-9.30	-17.10	5.55	0.86	0.05	0.14	0.90	-7.69	0.10	0.31
2	6	19	10.20	9.31	-9.30	-16.96	5.55	0.83	0.05	0.17	0.90	-7.65	0.10	0.35
4	6	20	10.20	9.26	-9.30	-16.95	5.55	0.79	0.05	0.21	0.90	-7.69	0.10	0.31

TABLE III

x(20)=9.4, y(20)=1, x(40)=11.8, y(40)=-5.

m (°)	σ (°)	K_c	x(0) (km)	y(0) (km)	v_x (km/h)	v_y (km/h)	x(20) (km)	y(20) (km)	E_x(20) (km)	E_y(20) (km)	x(40) (km)	y(40) (km)	E_x(40) (km)	E_y(40) (km)
0	2	16	7.2	6.85	5.1	-11.36	9.75	1.17	0.35	0.17	12.3	-4.51	0.50	0.49
0	4	18	7.2	6.79	5.1	-11.25	9.75	1.17	0.35	0.17	12.3	-4.46	0.50	0.54
0	6	20	7.2	6.75	5.1	-10.90	9.75	1.30	0.35	0.30	12.3	-4.15	0.50	0.85
2	4	20	7.2	6.76	5.1	-11.00	9.75	1.26	0.35	0.26	12.3	-4.24	0.50	0.76
2	6	20	7.2	6.74	5.1	-10.90	9.75	1.29	0.35	0.29	12.3	-4.16	0.50	0.84
4	6	20	7.2	6.73	5.1	-10.90	9.75	1.28	0.35	0.28	12.3	-4.17	0.50	0.83

observer moves on a straight line course at a speed of v_{ox} = 10.8 km/h, v_{oy} = 0 km/h for 10.5 min and then changes course by 135° and travels at a speed of v_{ox}=-7.65 km/h and v_{oy}= 7.65 km/h, as shown in fig. 10.

Simulation results for the three examples are presented in Tables I,II and III respectively. These tables summarize simulation results for various values of R and m. In these tables, K_c is the step at which convergence was attained. Also figs. 8-10 depict (apart from real target trajectories) the estimated target trajectories. Finally, results from the application of the pseudolinear filter (Aidala, 1979) to the scenario of example 3 with m=4 and R=36 are presented in figs. 11-12.

From these results, we conclude that the performance of the ALF is very good, even under adverse circumstances (high noise levels, large initial target range). Furthermore, it performs better than the pseudolinear filter.

We now turn our attention to the approach followed by Watanabe (1984).

Based on the model of eqs. (22)-(26), Watanabe developed a pseudolinear Partitioning filter. This filter's equations follow:

$$\hat{x}(k/k) = \hat{x}_n(k/k) + \Phi_n(k,0)\hat{x}_r(0/k) \quad (30)$$

$$P(k/k) = P_n(k/k) + \Phi_n(k,0)P_r(0/k)\Phi_n^T(k,0) \quad (31)$$

$$\hat{x}_n(k/k) = \Phi(k,k-1)\hat{x}_n(k-1/k-1) - M(k-1) \quad (32)$$

$$\hat{x}_r(0/k) = \hat{x}_r(0/k-1) - K_r(k)H(k)[\hat{x}_n(k/k) + \Phi_n(k,0)\hat{x}_r(0/k-1)] \quad (33)$$

$$K_r(k) = P_r(0/k-1)\Phi_n^T(k,0)H^T(k)S(k)^{-1} \quad (34)$$

$$S(k) = H(k)\Phi_n^T(k,0)P_r(0/k-1)\Phi_n^T(k,0)H^T(k)+1 \quad (35)$$

$$P_r(0/k) = [I-K_r(k)H(k)\Phi_n(k,0)]P_r(0/k-1) \quad (36)$$

$$\Phi_n(k,0) = \Phi(k,k-1)\Phi_n(k-1,0) \quad (37)$$

where

$$\hat{x}_r = [\hat{r}(0)\sin\beta(0) \;\; \hat{r}(0)\cos\beta(0) \;\; 0 \;\; 0]^T \quad (38)$$

$$\hat{r}(0) = [x^2(0) + y^2(0)]^{1/2}$$

with initial conditions

$x_n = 0$, $P_n = 0$, $P_r = I$, $\Phi_n(0,0) = I$.

Furthermore, Watanabe considered the possibility of incorporating a data compression mechanism into the algorithm. This mechanism consists of averaging m measurements before feeding them into the filter and feeding the filter with their average instead of the actual measurements. If we denote by $\bar{\beta}(ml)$ the mean value of measurements $\beta(k)$, $\beta(k+1), \ldots, \beta(k+m)$ which is fed into the filter at time ml, we have that

$$H(ml) = [\cos\bar{\beta}(ml) \;\; -\sin\bar{\beta}(ml) \;\; 0 \;\; 0]^T$$

and

$$\bar{\beta}(ml) = \frac{1}{m}\sum_{i=m(l-1)+1}^{ml} \beta(i), \qquad m \geq 1$$

where m indicates the compressing interval.

Then, the filter equations are modified as follows :

$$\hat{x}(k/k) = \hat{x}_n(k/k) + \Phi_n(ml,0)\hat{x}_r(0/ml) \quad (39)$$

$$P(k/k) = F_n(ml,0)P_r(0/ml)\Phi_n^T(ml,0) \quad (40)$$

$$\hat{x}_n(k/k) = \Phi(k,k-1)\hat{x}_n(k-1/k-1) - M(k-1) \quad (41)$$

$$\hat{x}_r(0/ml) = \hat{x}_r(0/m(l-1)) - K_r(ml)H(ml)[\hat{x}_n(k/k) + \Phi_n(ml,0)\hat{x}_r(0/m(l-1))] \quad (42)$$

$$K_r(ml) = P_r(0/m(l-1))\Phi_n^T(ml,0)H^T(ml)S(ml)^{-1} \quad (43)$$

$$S(ml) = H(ml)\Phi_n^T(ml,0)P_r(0/m(l-1))\Phi_n^T(ml,0)H^T(ml)+1 \quad (44)$$

$$P_r(0/ml) = [I-K_r(ml)H(ml)\Phi_n(ml,0)]P_r(0/m(l-1)) \quad (45)$$

$$\Phi_n(ml,0) = \Phi_m(ml,m(l-1))\Phi_n(m(l-1),0)(31) \quad (46)$$

where

$$\Phi_m(ml,m(l-1)) = \left[\begin{array}{cc|cc} 1 & 0 & m\Delta t & 0 \\ 0 & 1 & 0 & m\Delta t \\ \hline 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array}\right]$$

The above algorithm was simulated using a digital computer, in several situations. Representative results are shown in figs. 13-16, where the rms estimation error for three different renovating intervals (data compression intervals) averaged over 50 Monte Carlo runs is depicted. The scenario used involved the following : The initial range estimate was 6000m, the correspondeing bearing was 0°, the rms measurement noise level was 1° and the renovating interval took on the values m=10, m=20 and m=40.

From these figures, it can be seen that the pseudolinear partitioning filter performs well in estimating the target position and velocity. Moreover, the choice of the renovating interval plays an important role in the filter's performance. Other results not mentioned here but included in (Watanabe, 1984) indicate that increase of the observer maneuvers does not improve filter performance, that inreased noise levels affect the rate of convergence, and that the initial range estimate is also a significant parameter affecting filter performance.

VI. CONCLUSIONS

In this paper, a survey of the application of the Lainiotis filters to the problems of active and passive target tracking was conducted. The problems formulation was discussed, as well as the solutions proposed. Simulation results were presented, indicating the superiority of the partitioning approach over conventional techniques, such as the Extended Kalman Filter.

REFERENCES

Aidala,V.J. (1979). Kalman filter behavior in bearings-only tracking applications. IEEE Trans. on Aerosp. and Electr. Syst., AES-15, 29-39.

Aidala,V.J.and S.E.Hammel (1983). Utilization of modified polar coordinates for bearings-only tracking. IEEE Trans. on Auto. Contr., AC-28, 283-294.

Hawkes,R.M. and J.B.Moore (1976a). Performance bounds for adaptive estimation. Proceedings of the IEEE, 64, 1143-1150.

Hawkes,R.M. and J.B.Moore (1976b). Performance of Bayesian parameter estimators for linear signal models. IEEE Trans. on Auto. Contr., AC-21, 523-527.

Lainiotis,D.G. (1971). Optimal adaptive estimation : Structure and parameter adaptation. IEEE Trans. on Auto. Contr., AC-16, 160-170.

Lainiotis,D.G. (1976). Partitioning : A unifying framework for adaptive systems I : Estimation. Proceedings of the IEEE, 64, 1126-1143.

Lainiotis,D.G. and V.C.Moussas (1986). Adaptive filtering algorithms and target tracking. In Proceedings, International Conference on Identification and Pattern recognition - IPAR '86, Universite Paul Sabatier, Toulouse, France, 337-360.

Lindgren,A.G. and K.F.Gong (1978). Position and velocity estimation via bearing observations. IEEE Trans. on Aerosp. and Electr. Syst., AES-14, 564-577.

Murphy,D.J. (1970). Noisy bearings-only target motion analysis. Ph.D. Dissert., Dep. Elec. Eng., Northeastern University.

Nardone,S.E., A.G.Lindgren and K.F.Gong (1984). Fundamental properties and performance of conventional bearings-only target motion analysis. IEEE trans. on Auto. Contr., AC-29, 775-787.

Petridis, V. (1981). A method for bearings-only velocity and position estimation. IEEE Trans. on Auto. Contr. ,AC-26, 488-493.

Singer,R.A. (1970). Estimating optimal tracking filter performance for manned maneuvering targets. IEEE Trans. on Aerosp. and Electr. Syst.,AES-6,473-483.

Watanabe,K. (1984). Application of a pseudolinear partitioned filter to passive vehicle tracking. Int. J. of Syst. Sci., 15, 959-975.

Weiss,H. and J.B.Moore (1980). Improved EKF design for passive tracking. IEEE Trans. on Auto. Contr., AC-25, 807-811.