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A Novel Target Tracking Algorithm Using DAIRKF for Global MSE Optimization

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***Abstract* – This paper is based on the method to find out global optimality of mean square error (MSE) for multi target tracking. In the previous work as probabilistic data association algorithm (PDA) is used to track each target separately, it is not possible to track multi target at a time while in joint probabilistic data association algorithm (JPDA) it is possible to track multi target randomly in a cluster. JPDA algorithm provides good tracking results in less dense cluster but for denser cluster it is less efficient as compare to previous algorithms (e.g. JPDA is in sub optimal in sense). The DAIRKF algorithm which is advanced than JPDA in the MSE sense for multi target tracking in high dense cluster but DAIRKF does not optimize MSE globally. The DAIRKF algorithm is simple in computation while PDA, JPDA algorithms provide exponential terms which increases computational complexity. DAIRKF algorithm involves the correlation between different targets and gives better optimality; it integrates random coefficient matrices for distributed multi targets which are not global in the sense of MSE optimization. Distributed Kalman filtering algorithm with integrated random coefficient matrices is used to achieve the global optimization of MSE. The real time VHDL simulation provide results to evaluate tracking performance by estimating MSE in DAIRKF and JPDA algorithms, both give some about complement results in high and low dense cluster with respect to each other. Using global optimal technique for optimal MSE of Integrated Random Coefficient Matrices Kalman Filtering provides better results than DAIRKF algorithm. The simulated result shows that the proposed algorithm is better than all previous algorithms (PDA, JPDA, and DAIRKF). It gives global MSE optimization which is efficient to track multi target precisely and accurately.**

***Keywords* – PDA, JPDA, DAIRKF, Kalman Filtering, Global MSE Optimization.**

I. INTRODUCTION

Multitarget tracking is GPS and identification of object in radar. This is a set of estimates of dynamical states of objects, to a set of measurements generated by a sensing device as radar or an optical sensor [5]. There are many algorithms are designed to obtain accurate target tracking; like PDA, JPDA DAIRKF etc. but some limitations of these algorithms because these are not more appropriate to give optimum tracking results.

In PDA and JPDA association performance is described by a function of normalized object density.

$$\beta_{j,t} = \sum_{j=1}^{m} \left(x_k \mid y_1^k \right)$$

Whenever there is miss association or association defined by an exponential linear law, PDA can track only one target at a time while JPDA can track multi-target but for every object it is necessary to put appropriate weight for exact estimation. All algorithms depend on the assumptions for the targets which are distributed randomly and this distribution it to be a Poisson's distribution, noise is Gaussian noise (process and Measurement noises). JPDA is more advanced then PDA; In JPDA exponential terms are involved, so in case of high dense cluster it is less efficient to track the target [2]. JPDA is appropriate only when target density is less.

On the other hand DAIRKF algorithm is more appropriate because it gives better response as compared to JPDA in high dense cluster [1]. DAIRKF is based on Kalman filtering which works on prediction [3-4] integrated random coefficient matrices are formed for prediction and measurement conditions. Prediction and measurement are taken for each and every sample of target at a time. All data for a target is associated for different targets at a time.

Basically DAIRKF is estimate in MSE sense but not globally optimal. Target measurement is easy in DAIRKF because computation of matrices of discrete integrated samples for different targets is easier.

Here in this paper global MSE optimization is presented which gives more appropriate results than DAIRKF, MSE is globally optimized measurement noise. Global optimization technique is used to optimize the error (measurement noise) [11], for this linear model is preferred which is linear matrix inequality problem with sufficient global optimality conditions.

II. PROBLEM FORMULATION

In this section the multi target tracking problem is presented as-

The Kalman filter state equations [4].

$$X_{k+1} = F_k X_k + v_k \qquad (1)$$

$$Y_k = H_k X_k + w_k \qquad (2)$$

Equation (1) & (2) are known as prediction and measurement equations, Xk is priori (prediction) matrix of different target. In order to make nation used amenable first of all single cluster is assumed with targets (t = 1……T) and measurements are 'm' for a given time 'k'. The above equation s (1) & (2) are modified [1] as-

$$X^t_{k+1} = F_k X^t_k + v^t_k \qquad (3)$$

$$Y^t_{k,J} = H_k X^t_k + w^t_{k,J} \qquad (4)$$

Where, $X^t_k \in Q^R$ and $v^t_k \in Q^R$ also these are defined as system state and noise. Noise is assumed to be a Gaussian noise. $Y^t_{k,J} \in P^S$ and $w^t_{k,J} \in P^S$ are define as measurement state and measurement noise and it is also Gaussian which is not correlated with other noise F_k and H_k are random coefficient matrices .

The result oriented JPDA algorithm described as fallows.

1. First of all for a particular value of k generate N samples from all targets (t=1……T)
$\left\{ x_0^{(i),1} .... x_0^{(i),T} \right\} = \left\{ x_0^{(i),T} \right\}_{i=1}^{N}$
2. For each particle calculation of weights for each and every measurement to track association, normalized density is $\beta^i_{k,j}$ and $\beta^0_{k,j}$ denotes the false measurement
3. Generate new set $\left\{ x_k^{(i),1:T} \right\}_{i=1}^{N}$ by resampling with replacement N times.
4. Predict new particle.
5. Increase k and iterate from second step

The DAIRKF algorithm is something different from the JPDA in computational sense. In JDPA exponential terms are computed but in DAIRKF linear matrix model is computed which is easy to compute when cluster is highly dense.

The (3) & (4) are modified for measurement as-

$$X_{k+1} = F_k X_k + v_k \tag{5}$$

$$Y_k = \bar{h}_k X_k + \tilde{w}_k \tag{6}$$

Where,

$\tilde{w}_k = w_k - \bar{w}_k$, optimal error

$\bar{w}_k = E[w_k]$, mean of noise

$\bar{h}_k = E[h_k]$, mean of integrated random coefficient matrices

For single tracking target tracking-

$X_k = \{ x_k^1, x_k^2, x_k^3 .... x_k^N \}'$; for t=1 and N is the no of samples

For multi-targets –

$X_k^t = \{ X_k^{1'}, X_k^{2'}, X_k^{3'} .... X_k^{T'} \}'$; for t =1…..T

$v_k^t = \{ v_k^{1'}, v_k^{2'}, v_k^{3'} .... v_k^{T'} \}'$

$y_k^t = \{ y_k^{1'}, y_k^{2'}, y_k^{3'} .... y_k^{T'} \}'$

and

$w_k^t = \{ w_k^{1'}, w_k^{2'}, w_k^{3'} .... w_k^{T'} \}'$

$h_k = \{ h_k^{1'}, h_k^{2'}, h_k^{3'} .... h_k^{T'} \}'$, h_k is a diagonal matrix again

$y_k^t - \bar{h}_k X_k = \tilde{w}_k^t$

Measurement $Y_k \in P^S$ and $w_k \in P^S$ is the measurement and measurement noise.

The different statistical properties [1] are as –

$\{ F_k, H_k, v_k, w_k, k = 0,1,2,...... \}$, are sequence of independent X_k and $\{ F_k, H_k, v_k, w_k, k = 0,1,2,...... \}$, are sequence of random variables.

The mean of any dynamic function can be calculated by taking first expectation of that function and double expectation gives probability of data.

Under the additional conditions on the system dynamics, the Kalman filter dynamics converges to a steady state filter and steady state gain is derived [1-3].

Filter State Estimate = Predicted State Estimate + gain * error

or $X_{k/k} = X_{k/k-1} + K_k \left(y_k - \bar{h}_k X_{k/k-1} \right)$

$$K_k = p_{k/k} \bar{h}_k' \tilde{R}_{w_k}^{-1}$$

$$p_{k/k} = F_k p_{k-1/k} F_k' + R_{v_k} = \left(I - K_k \bar{h}_k \right) p_{k/k-1}$$

In case of DAIRKF the error is sub optimal, iterated and filters out but it cannot be so optimal in global sense. The global optimality is achieved by obtaining the mean value which is near about to the error.

III. Global Optimization of Error

This optimization is done by calculating the appropriate value of mean error (measurement which is error near about to the measurement error). Here linear model is adopted to calculate the mean error. In this model a error function is defined as follows -

$$\min_{w_k \in P^s} w_k' A w_k + 2a' w_k + \alpha = f(w_k)$$

Now for m measurements-

$g_i(w_k) = w_{k_i}' B_i w_{k_i} + 2b_i' w_{k_i} + \beta_i$; i =1…….m

& $d_j(w_k) = w_k' E_j w_k - 1$; j=1……..n

E_j can be calculated by above equation.

as $g_i(w_k) = 0$ and $d_j(w_k) = 0$

$$\left(w_k - \bar{w}_k \right)' \left(A + \sum_{i=1}^{m} \mu_i B_i + \sum_{j=1}^{n} \gamma_j E_j \right) \left(w_k - \bar{w}_k \right) \prec 0$$

The, $\bar{w}_k$ for which this condition is satisfy known as necessary and sufficient global optimality condition. This is known as KKT point and condition is defined error as global optimality characterization [11].

The optimal error is defined as-

$$\tilde{w}_k = w_k - \bar{w}_k$$

As the, $\bar{w}_k$ is nearest to w_k then $\tilde{w}_k$ will be minimal or optimal and measurement will be more accurate.

Mean square error varriance is calculated as-

$$E\left[\tilde{w}_k \tilde{w}_k' \right] = \sigma^2_{\tilde{w}_k}$$

This $\tilde{w}_k$ is used for iteration of calculate more precise result in the measurement stage. Optimization of error gives better result even in high dense cluster to identify multi-targets.

The global error optimization in multi target tracking is computed by sequential mathematical procedure for optimality of error which is implemented in real time VHDL. Kalman filtering dynamic linear model provides the optimal error and for minimization of error global optimality algorithm is proposed. The flow chart which is given below for complete algorithm is used to track multi-target accurately than the DAIRKF.

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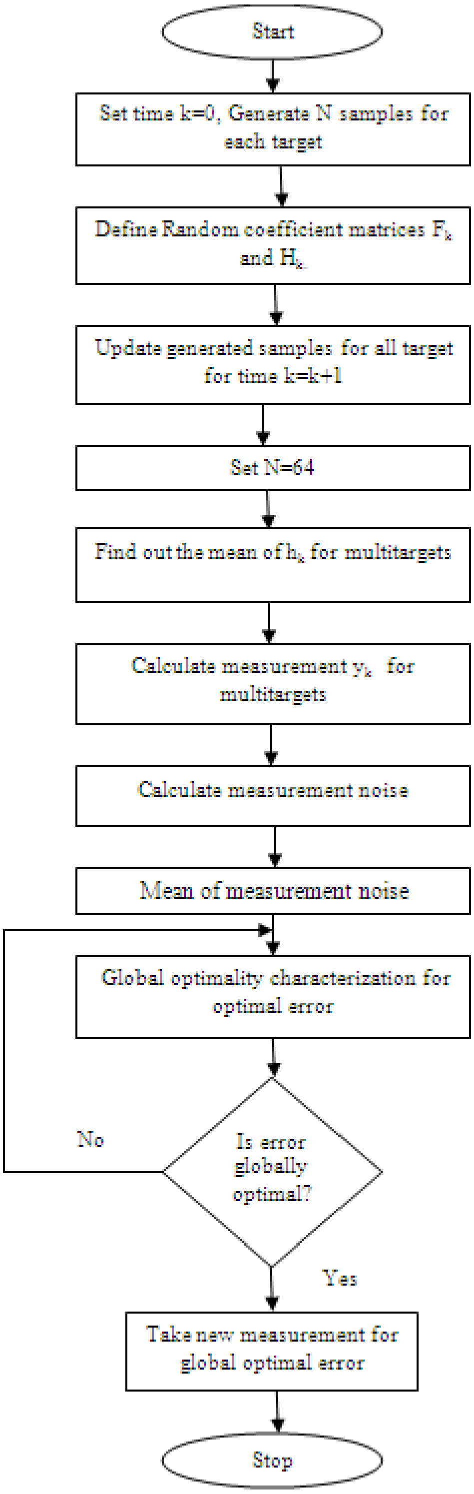
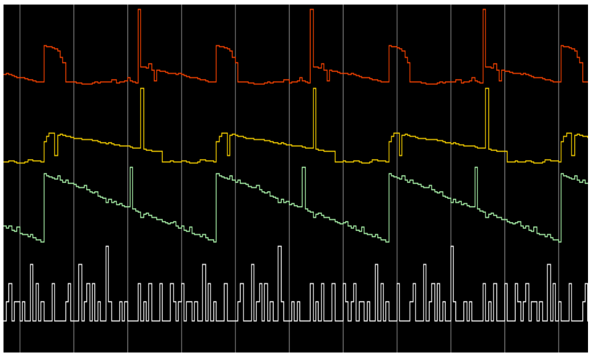


Fig.1. The flow chart of multi-target tracking with global MSE

IV. Simulations Results

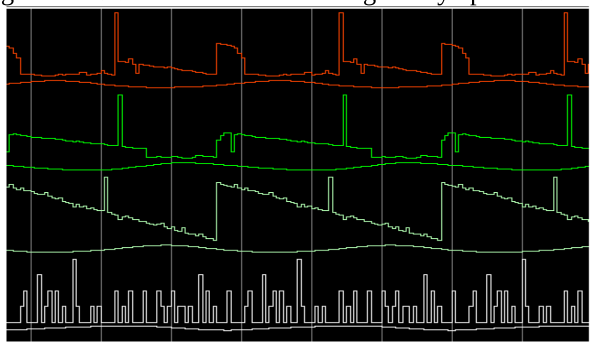
In this section, VHDL real time simulation results are used to assess the performance of multi tracking algorithms. Here four targets are taken as multi targets, all targets are generated, and tracking algorithms are applied to track these targets, all simulation results are obtained in real time dynamic Kalman filtering model. There are results related to DAIRKF and globally optimized measurement error and measurement for multi targets are shown-



Time k

Fig.2. DAIRKF error for four targets

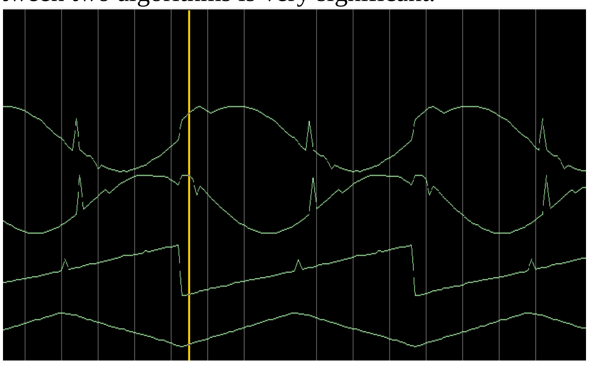
The simulation results in fig.3 shows the errors for all target tracking results, here it is clear that error of measurement in global optimal algorithm for multi targets is very less than the measurement error of DAIRKF algorithm i.e. measurement error is globally optimal.



Time k

Fig.3. DAIRKF and global errors are in parallel for four targets

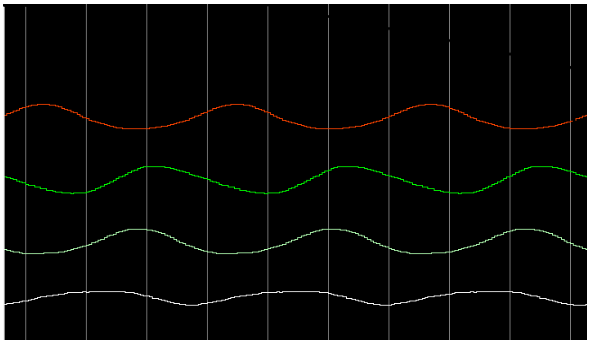
The tracking results of DAIRKF algorithm are shown in Fig.4 and it is seen that tracking results for each target are not so good but gives satisfactory result. The difference between two algorithms is very significant.



Time k

Fig.4. DAIRKF outputs

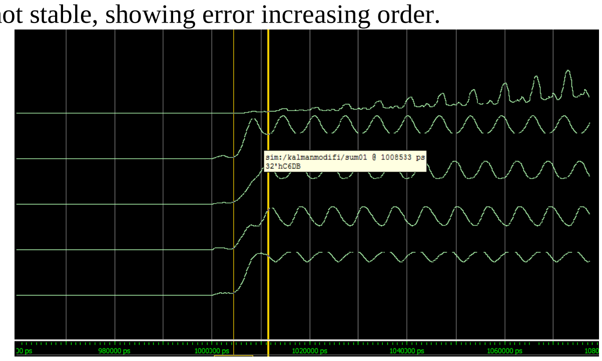
The tracking results of all targets by using global optimality characterization are very precise as compare to DAIRKF algorithm. So this technique is more power full to track any dynamic object.



Time k

Fig.5. Filtered output for global

The global optimal response related with time is shown by the fig.6. The first waveform is for DAIRKF but all the other four waveforms are for global optimal condition which has constant minimal errors. The first waveform is not stable, showing error increasing order.



Time k

Fig.6. Time response of the different adapted algorithms

V. Conclusion and Future Scope

In this paper global optimization algorithm is used for multi target tracking. It is more power full than all other (PDA, JPDA and DAIRKF) algorithms, the simulation results show that the measurement error in DAIRKF algorithm is not optimum as we want for efficient tracking. In integrated random coefficient Kalman filtering with global MSE optimization algorithm the error is optimized so that any target can be identified very clearly. The error in global optimality algorithm is minimized by selecting the appropriate KKT mean error point. The further improvement in measurement can be possible with finding the new KKT point for mean of global optimal error to fined absolute optimal error. This gives better results in any type of environment and clutter. From fig.6 we can say that proposed technique is more appropriate.

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