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Real-Time VHDL Implementation of Advanced Multitarget Tracking Algorithm

Swarnim Naik
M.Tech Scholar
T.I.T, Bhopal, M.P, India
swarnim.naik@gmail.com

Sandip Nemade
Associate Professor
T.I.T, Bhopal, M.P, India
nemadesandip@yahoo.com

Vikas Gupta
Associate Professor
T.I.T, Bhopal, M.P, India
vgup24@yahoo.com

***Abstract*— A novel tracking algorithm presented in this paper is more advanced than other algorithms which have been presented before. The target tracking algorithm is implemented very clearly with the VHDL program. The object is defined by its samples. In the previous decade, PDA and JPDA algorithms are used for single target and multi target tracking of respectively. There is more complexity for dense target density in a cluster. So it is need to compute the data within limited time and complete the algorithm which is implemented early. The advancement of tracking algorithm is going on time to time. After the PDA and JPDA algorithms DAIRKF algorithm is developed which is more accurate and easy to implement in VHDL and also the present algorithm is implemented in Real- time. The advanced DAIRKF algorithm is developed to track the multi target in high dense cluster very clearly.**

***Keywords* – PDA, JPDA, Model-based Predictive Controllers (MPCs), DAIRKF, Kalman Filtering, Advance Error Optimization, VHDL.**

I. Introduction

Proposed advance target tracking algorithm is appropriate for multi target tracking. In PDA, only one target can be tracked at a time, here normalized density of a target shows the presence of a target in a region of cluster. The Bayesian's algorithm is used in PDA and JPDA to represent the probability of a target in a specified environment or region. If uncertainty about the measurement origin decreases, the accuracy of the state estimate must be very accurate for each target [3]. The PDA and JPDA algorithm creates a weighted average of all received measurement came from the target. The JPDA algorithm tracks multi target at same time parallely. In denser cluster it is difficult to implement the computation utilizes more time with poor accuracy. This is the major drawback. This problem is solved by DAIRKF algorithm which is very less complex and easy to implement this algorithm [1].

All the tracking algorithms are completely based on Kalman filtering which is recursive in nature. The Kalman Filter has many applications, e.g. in dynamic positioning of ships where the Kalman Filter estimates the position and the speed of the vessel and also environmental forces. These estimates are used in the positional control system of the ship. The Kalman Filter is also used in soft-sensor systems used for supervision, in fault-detection systems, and in Model-based Predictive Controllers (MPCs) which is an important type of model-based controllers [10].

The optimal estimate is produced by state estimation in Kalman Filter which senses that the mean value of the sum (actually of any linear combination) of the estimation errors gets a minimal value. The Kalman Filter gain is a time varying gain matrix [7]. Usually it is necessary to fine-tune the Kalman Filter when it is connected to the real system. The process disturbance (noise) auto-covariance Q and/or the measurement noise auto-covariance R are commonly used for the tuning. However, since R is relatively easy to calculate from a time series of measurements using some variance function, we only consider adjusting R here.

The estate estimate and measurement is defined as measurement noise if there are n targets is presented in a clustered and all targets are tracked at a time i.e. multi target tracking is done. This tracking procedure is characterized by mathematical expressions.

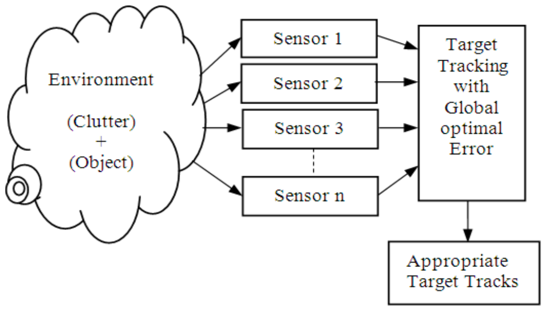

Fig.1. General Model of advanced multi target tracking with sensor fusion

The Fig.1 shows the general model of advanced multi target tracking with global optimal error. All the sensors capture the status of the object in cluttered environment and some random noise is introduced during measurement processes in all the regions. The noise is optimised globally by global optimal characteristic [15] and hence most appropriate target tracking takes place. In case of multi sensor target tracking the behaviour of all sensors is integrated and defines as fusion [10].

II. Problem Formulation

The mathematical relation is found by pedicle of next state estimate with the relation of previous. Estate estimate with Gaussian noise and measurement is the relationship of previous state estimate with same permissible measurement noise, defined as Kalman filtering for single target. These equations are also known as key equations to estimate measurement of a thing present randomly in a region. As the filtering processes is iterative let in measurements are taken during each measurement a Gaussian measurement noise is detected and assured that is random and is defined as white noise.

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

and

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

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These equations are also known as key equations for measuring of an object with defined prediction. X_k is priori (prediction) column matrix of different targets [3].

For 'm' measurements the measurement equation is represented as in the all past algorithms targets predicted signals are presented in the form of sampled data and this is elements of matrix whether it is known row of square matrix.

Let for single target 'm' measurement is taken and let 'n' targets are available in a clusture then above equations can be written as-

$$X^t{}_k = F_k X^t{}_{k-1} + v^t{}_k \quad (3)$$

And

$$Y^t{}_{k,J} = H_k X^t{}_k + w^t{}_{k,J} \quad (4)$$

Where $X^t{}_{k-1} \in Q^R$ and $v^t{}_k \in Q^R$, these are defined as system state and noise and $Y^t{}_{k,J} \in P^S$ and $w^t{}_{k,J} \in P^S$ are define as measurement state and measurement noise. Here t shows the targets Noise is assumed to be a Gaussian or white noise. Updation of state vector is proceeding with each and every discrete time.

The past general steps of DAIRKF algorithm to track target is-

1. Generate defined no of samples of a target as prediction.
2. Measurement is taken for predicted value of specified target.
3. Update state estimate with time.
4. Again measurement is taken (thus a matrix of all measurements is found)
5. Iterate process for j = 1……….m

The DAIRKF algorithm is advance than all other previous algorithms in computational and its simplicity [1].

The measurement equations (4) is written as-

The State updation

$$X_k = F_k X_{k-1} + v_k$$

and measurement

$$Y_k = \bar{h}_k X_k + \hat{w}_k$$

Where,

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

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

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

For multi target tracking all the matrices related to its state vector, measurement, process error, measurement error and integrated random coefficient are written.

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

For multi-targets –

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

$$v_k^t = \{v_k^{1'}, v_k^{2'}, v_k^{3'} \ldots\ldots\ldots\ldots v_k^{n'}\}'$$

$$y_k^t = \{y_k^{1'}, y_k^{2'}, y_k^{3'} \ldots\ldots\ldots\ldots y_k^{n'}\}'$$

and

$$w_k^t = \{w_k^{1'}, w_k^{2'}, w_k^{3'} \ldots\ldots\ldots\ldots w_k^{n'}\}'$$

$h_k = \{h_k^{1'}, h_k^{2'}, h_k^{3'} \ldots\ldots\ldots\ldots h_k^{n'}\}'$, h_k is a diagonal matrix again

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

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].

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

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

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

III. Error Optimization

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. 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 error function is defined as follows [15-17]-

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

Now for m measurements-

$g_i(w_k) = w_k' B_i w_{k_i} + 2b_i' w_{k_i} + \beta_i$; 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 $d_j(w_k) = 0$

The optimality characterization is described by the equation given bellow.

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

The appropriate value of $\bar{w}_k$ is so chosen so that this condition is satisfy known as necessary and sufficient global optimality condition. This value of $\bar{w}_k$ for which the condition satisfies known as KKT point and condition is defined error as global optimality characterization [11].

The optimal error is defined as-

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

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

Mean square error variance is calculated as-

$$E\left[\hat{w}_k \hat{w}_k'\right] = \sigma_{\hat{w}_k}^2$$

This $\hat{w}_k$ is used for iteration of calculate more accurate results in the measurement stage. Optimization of error gives better result even in high dense clusture to identify multi-targets. This algorithm is described in steps as-

1. Set k=0 and generate N samples for all targets t = 1…n.
2. Define random coefficient matrices F_k and H_k as upper half and lower half matrices,
3. Set N=8 for no of samples.
4. Update samples for time k.
5. Take measurement for time k then for k+1 in iterative procedure.
6. Integrate all measurements and state vectors for all the targets parallel.
7. Find mean of converges random coefficient matrix and integrated state vector.
8. Precede global optimal error theorem and find appropriate value of mean at which error is optimal.

9. Put mean value of state vector in previous measurements and go for iteration to calculate advance measurement.

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.

IV. Simulation Results

The VHDL results related to predicted and measurement outputs for all the targets are shown here, the targets are just specified by particular signal. Target 1 is just represented by sinusoidal wave, target 2 is also represented by sinusoidal with 180^0 out of phase with the first target and target 3 and target 4 are represented by saw tooth and triangular wave respectively in Fig.2.

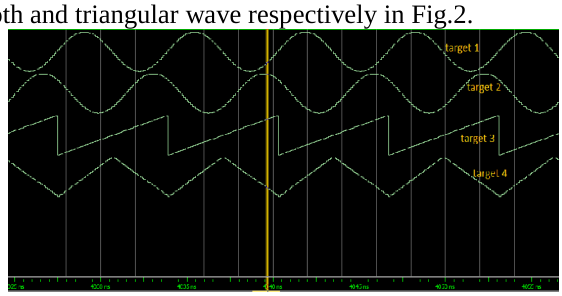

Fig.2. All real time targets are represented by its particular wave

First of all target signals are sampled at a particular sampling rate. Fig3 shows the sampled signals of all targets. Here for simplicity eight no. of samples are taken.

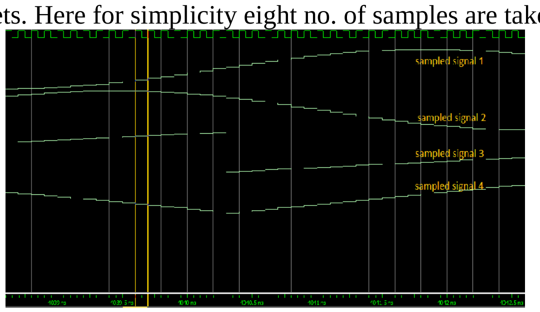

Fig.3. Sampled signals are shown in the above figure

The measurement outputs of the DAIRKF algorithm are shown in figure 4 for the all the targets. From the results it is very clear that measurement is not so identical as compared to original signals i.e. random error is present in the measurements.

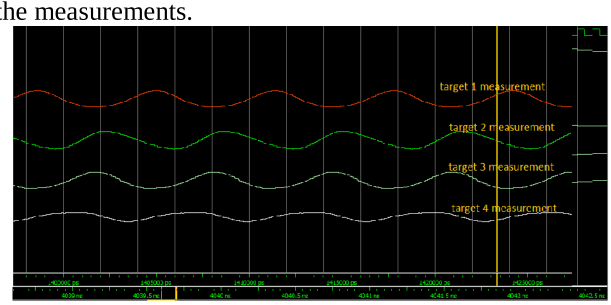

Fig.4. Output signal of DAIRKF algorithm waveform for the measurement

The measurement output signals in global optimality condition for all targets separately is shown in the figure 5, from this figure it is very clear that the measured output is find and just identical with the original signals with some extent of error. These results are more accurate as compared to the DAIRKF results.

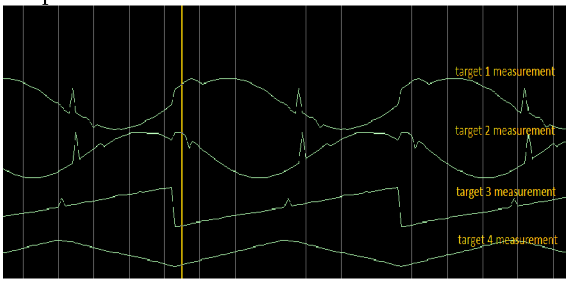

Fig.5. Output obtained in proposed advanced algorithm for all targets

The error in both algorithms measurement outputs is shown below in the figure6; from top to bottom the first four signals show the errors in the 1st, 2nd, 3rd, and 4th respectively, the 5th, 6th, 7th and 8th signals show the error of measurements for global optimal algorithm.

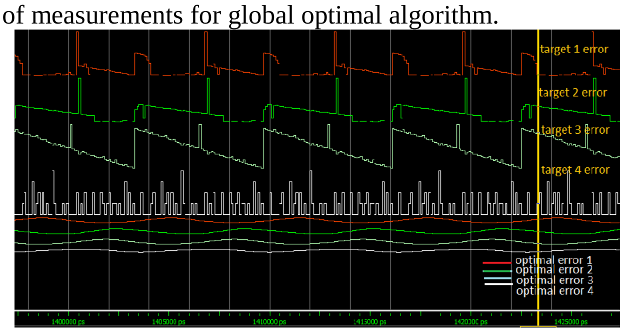

Fig.6. DAIRKF error and global optimal error

From the above results it is very clear that error of advance algorithm for multitarget tracking is optimal as compared to all previous algorithms.

V. Conclusion and Future Scope

Proposed algorithm is used to track target more accurately in which error is minimal. This algorithm is more efficient as compared to all algorithms used before this; the simulation results clarify the accuracy and validity of algorithm. 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 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.

References

[1] Yingting, Luoyunmin, Zhuxiaojing, Shenenbin Song, “Novel Data Association Algorithm Based on Integrated Random Coefficient Matrices Kalman Filtering” IEEE transactions on aerospace and electronic systems vol. 48, no. 1 january 2012.

[2] G. Welch, G. Bishop, “An Introduction to the Kalman Filter, *Chapel Hill, NC 27599-3175.*

[3] Kusha Panta, Ba-Ngu Vo, Sumeetpal Singh **“**Novel Data Association Schemes for the Probability Hypothesis Density Filter” *IEEE transactions on aerospace and electronic systems vol. 43, no. 2 april 2007.*

[4] M.I. Ribeiro, “Kalman and Extended Kalman Filters: Concept, Derivation and Properties”, *feb. 2004.*

[5] Eric A.Van, Rudolf van der Marwe “Liture On Unscended Kalman Filter”

[6] P.D.Hanlon, P.S.maybeck, “Characterization of Kalman Filter Residuals in the Presence of Mismodelling”, *IEEE Trans. On aerospace and electronics systems, Vol. 36, No. 1, January 2000.*

[7] P.D.Hanlon, P.S.maybeck, “Multiple-Model Adaptive Estimation Using a Residual Correlation Kalman Filter Bank” *IEEE transactions on aerospace and electronic systems vol. 36, no. 1 january 2000.*

[8] Tsachy Weissman, Abhishek Arora “Interpreting Forward/Backward recursions-Kalman Filtering” EE378A Statistical signal processing, part A 19 january 2011.

[9] Mohinder S. Grewal, and James Kain “Kalman Filter Implementation with Improved Numerical Properties” IEEE transactions on automatic control, vol. 55, no. 9, september 2010.

[10] Jehangir Khan Smail Niar Atika Menhaj Yassin Elhillali “Multiple Target Tracking System Design for Driver Assistance Application” IEEE transactions on automatic control, vol. 42, no.15, september 2010.

[11] Jwu-Sheng Hu, and Chia-Hsing Yang “Second-Order Extended Kalman Filter for Nonlinear Discrete-Time Systems Using Quadratic Error Matrix Approximation” IEEE transactions on signal processing, vol. 59, no. 7, july 2011.

[12] Gerasimos G. Rigatos “A Derivative-Free Kalman Filtering Approach to State Estimation-Based Control of Nonlinear Systems” IEEE transactions on industrial electronics, vol. 59, no. 10, october 2012.

[13] Julien Diard_, Pierre Bessière, and Emmanuel Mazer “A survey of probabilistic models, using the Bayesian Programming methodology as a unifying framework” BIBA European project (IST-2001-32115).

[14] Goberna M.A., Jeyakumar V., Li G., L_opez M.A. “Robust linear semi-infinite programming duality under uncertainty” ARC Discovery Project DP110102011 of Australia and by MICINN of Spain, Grant MTM2008-06695-C03-0.

[15] G.Li, “Global Quardratic Minimization over Bivalent Constraints: Necessary and Sufficient Global Optimality Condition”.

[16] Zoran Salcic, -Ruey Lee “Scalar-Based Direct Algorithm Mapping FPLD Implementation of a Kalman Filter” IEEE transactions on aerospace and electronic systems vol. 36, no. 3 july 2000.

[17] V. Jeyakumary and G. Y. Liz “Strong Duality in Robust Semi-De_nite Linear Programming under Data Uncertainty” AMS subject classi_cation. 90C22, 90C25, 90C46 March 1, 2012.