A Modified Track-Oriented Multiple Hypothesis Tracking Approach for Coastal Surveillance

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Abstract:

In coastal surveillance scenario, multiple targets of varying cross-sections have to be tracked in sea clutter environment within territorial waters. Conventional data association algorithms such as Global Nearest Neighbour (GNN) & Joint probabilistic data association (JPDA) perform well when targets are spatially separated without overlapping gates and clutter density is low. In high clutter environment when targets are moving closely these methods result in inaccurate state estimates, track coalescence & track loss. Conventional multiple hypothesis tracking methods are computationally complex as number of targets to be tracked are high in coastal waters. In this paper, IMM (Interactive Multiple Model) Kalman filter based Track-oriented Multiple Hypothesis Tracking (TO-MHT) approach is proposed for improving data association for closely moving & manoeuvring targets in sea clutter with optimization of computational speed and accuracy of derived state estimates. The range and azimuth spread of radar measurements are utilized in data association for improving track-measurement association accuracy & reducing computation load on TO-MHT algorithm. Automatic Identification system (AIS) data from vessels fitted with AIS transponder are decoded and utilized in data association to improve track maintenance.

Keywords – Track oriented Multiple Hypothesis tracking, Interacting Multiple Model, Automatic Identification system.

I. INTRODUCTION

Coastal surveillance & vessel traffic monitoring systems have gained paramount importance with objective to achieve maritime domain awareness of territorial waters and Exclusive economic zone (EEZ) of every nation. Track while scan (TWS) radars with Automatic Identification System (AIS) receivers / transponders are generally employed along coastline for detecting & tracking sea surface contacts of varying size i.e. from small fishing vessel to large tankers & cargo ships.

This multiple target tracking scenario involves detection of surface contacts in presence of sea clutter, initiating surface tracks, associating radar measurements with confirmed tracks from scan to scan and updation of state estimates using interacting multiple model (IMM) Kalman filters as shown in Fig 1.

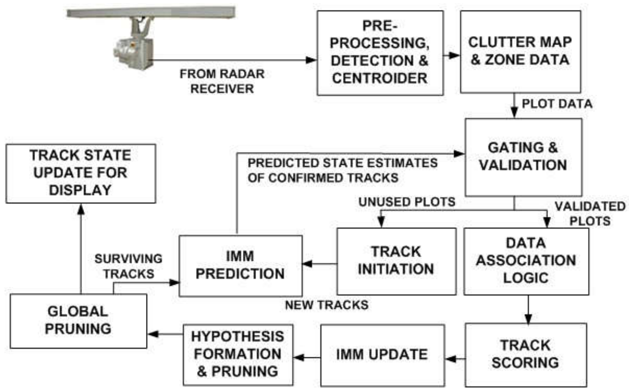

Fig 1: IMM TO-MHT Tracker operation

Once tracks are initiated, the state estimates of each track are use in IMM Kalman filter module for predicting position & kinematic parameters in next scan interval. A validation region commonly called track gate is computed in order to choose radar measurements obtained in each scan for data association check with tracks. The data association step in tracking operation decides whether radar measurements obtained in each scan should be associated with existing tracks or used for initiating new tracks or be rejected as clutter.

The Global Nearest Neighbour [3][4] approach maintains the single most likely hypothesis about all of the measurements received in the past. Global nearest neighbour algorithm forms a validation matrix containing all measurements within validation region (within gate) of each confirmed target. Normalized statistical distance of predicted position of target to the measurement under consideration will form the cost metric:

$$d_{ij} = \sqrt{(\vartheta'(k+1)S^{-1}\,(k+1)\vartheta(k+1))} \qquad (1)$$

This assignment matrix is solved for obtaining unique track to measurement association which minimizes the sum of overall assignment cost.

The Joint Probabilistic Data Association approach [3][4] is soft decision equivalent of GNN. The Gaussian likelihood function associated with the assignment of all measurement ‘M_i’ to tracks ‘T_j’ are computed:

$$L_{ij} = e^{-\frac{d_{ij}^2}{2}} / (2\pi)^{\frac{M}{2}} \sqrt{|S_{ij}|} \quad (2)$$

The Gaussian likelihood function associated with the assignment of measurement ‘M_i’ to false alarm (FA) is computed:

$$L_{i0} = \beta_{FA}(1 \quad P_D) \quad (3)$$

Where, $\beta_{FA} = \frac{N_{FA}}{V_G}$ is density of false alarms, N_{FA} is number of false alarms & V_G is volume of gate. The hypothesis for current scan measurement to track associations are formed. Hypotheses probabilities are calculated and then assignment probabilities for each track to measurement are calculated. Assignment matrix is formed with track to measurement association probability as cost metric. This is solved for obtaining unique track to measurement association which maximized the sum of overall assignment cost.

Both of approaches explained above do not maintain any hypotheses from scan to scan. Hence ambiguities arising due to multiple common measurements in each scan interval for closely moving tracks are not solved in optimal way. This results in inaccurate kinematics in track state estimates and track loss.

The Multiple hypothesis tracking (MHT) approach considers multiple association hypotheses over ‘N’ scan intervals; typically N varies from 3 to 5 scans. This scheme assumes that any uncertainty is perfectly resolved after N time steps. The N last ancestors of each hypothesis must be stored. The number of such possible combinations with ‘M’ measurements in ‘N’ scans is:

$$C_M^N = \frac{N!}{M!(N-M)!} \quad (4)$$

There are two principal implementations of MHT, namely:

- Hypotheses / Measurement oriented MHT &
- Track oriented MHT

In hypotheses oriented approach [5], exponential hypotheses growth can be limited by retaining only N best hypotheses from each scan in accordance with Murty's method. This method is computationally more complex when number of measurement to target association possibilities increase in cluttered environment when targets are moving closely.

II. *TRACK ORIENTED MULTIPLE HYPOTHESIS TRACKING WITH IMM*

Track-oriented MHT [2], will learn the trajectories of all targets that are visible to the radar system. Here, tracks are initiated updated and stored before being formed into hypotheses. The scoring process consists of comparing the likelihood that the track represents a true target versus the likelihood that it is a collation of false alarms. Thus, unlikely tracks can be deleted before the next stage in which tracks are formed into hypotheses.

The track-oriented approach recomputes the hypothesis using the newly updated tracks after each scan of data is received. Rather than maintaining and expanding hypotheses from scan to scan, the track-oriented approach discards the hypotheses formed on scan ‘k-1’.The tracks that survive pruning are predicted to the next scan ‘k’ where new tracks are formed, using the new observations, and reformed into hypotheses. Except for the necessity to delete some tracks based upon low probability or N-scan pruning, no information is lost because the track scores, which are maintained, contain all the relevant statistical data.

Track scoring [4], is done using log-likelihood ratio which is computed as shown below:

$$(k) = \log[LR(k)] = \sum_{k=1}^{K}[LLR_K(k) + LLR_S(k)] + \log[\ _0] \quad (5)$$

where the subscript K denotes kinematic and the subscript S denotes signal. It is assumed that the two are statistically independent.

$$_0 = \frac{P_0(H_1)}{P_0(H_0)} \quad (6)$$

where H_1 and H_0 are the true target and false alarm hypotheses. The likelihood ratio for the kinematic data is the probability that the measurements are a result of the true target divided by the probability that the measurements are from false alarm.

$$_k = \frac{p(D_k|H_1)}{p(D_k|H_0)} = L_{ij} \quad \ldots \textit{from } (2)$$

The following are rules for each measurement:

- Each measurement creates a new track.
- Each measurement in each gate updates the existing track. If there is more than one measurement in a gate, the existing track is duplicated with the new measurement.
- All existing tracks are updated with a missed measurement, creating a new track.

Hypothesis Formation:

In MHT, a valid hypothesis is any compatible set of tracks. In order for two or more tracks to be compatible, they cannot share same observations or plots. The track-oriented approach recomputes hypothesis, [4] using the newly updated tracks after each scan of data is received. The hypotheses formation step is formulated as a mixed integer linear programming (MILP) framework and solved using GNU Linear programming kit (GLPK) [11]. The MILP formulation is constructed to select a set of tracks that maximizes total score, such that;

1. No two tracks in formulated hypotheses have the same track number. &
2. No two tracks are associated with same observation for any scan.

The algorithm solves for ‘M’ (typically 2) best hypotheses, in descending order of score which enables tracks to be preserved from alternate hypotheses that may be very close in score to the best.

Track Pruning:

N-scan pruning approach is carried out at each step using the last ‘*n’* scans of data (typically 3 or 5) [4] [11]. The pruning method preserves:

1. Tracks with the *n* highest scores.
2. Tracks that are included in the ‘M’ best hypotheses.

3. Tracks that have both the track number and the first '*p*' measurements found in the 'M' best hypotheses.

The parameters *M, n &, p* are tuned to improve performance. The objective with pruning is to reduce the number of tracks as much as possible while not removing any track that should be part of actual true hypotheses.

The IMM Algorithm:

In target tracking literature, a moving target is usually modeled by the stochastic system, [3] [4] [10]

$$x_{k+1} = F_k . x_k + G_k . u_k + v_k \qquad (7)$$

where x_k is the state vector, u_k is an acceleration input, and v_k is process noise.

The measurement process is usually modeled by

$$y_k = H_k . x_k + w_k \qquad (8)$$

where x_k is the state vector, and w_k is measurement noise. The process noise v_k and the measurement noise w_k are mutually independent zero-mean, white Gaussian random sequences with covariance matrices $Q(k)$ and $R(k)$ respectively. The matrices *F, G, H, Q* and *R* are assumed known and can be time varying. The IMM (Interacting multiple models) estimator is used to predict and update the current start of all targets kept under track, using more than one state transition model.

Total number of target manoeuvre models used are three (*r* =3) namely;

a) **Constant velocity model:** Describes essentially non-manoeuvring state.

$$\begin{matrix} x_{k+1} \\ x_{k+1} \\ y_{k+1} \\ y_{k+1} \\ y_{k+1} \\ y_{k+1} \end{matrix} = \begin{matrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{matrix} \quad \begin{matrix} x_k \\ x_k \\ y_k \\ y_k \\ y_k \\ y_k \end{matrix} \qquad (9)$$

b) **Constant acceleration model**: Describes a steady-state manoeuver.

$$\begin{matrix} x_{k+1} \\ x_{k+1} \\ y_{k+1} \\ y_{k+1} \\ y_{k+1} \\ y_{k+1} \end{matrix} = \begin{matrix} 1 & T & 0 & 0 & \frac{T^2}{2} & 0 \\ 0 & 1 & 0 & 0 & T & 0 \\ 0 & 0 & 1 & T & 0 & \frac{T^2}{2} \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{matrix} \quad \begin{matrix} x_k \\ x_k \\ y_k \\ y_k \\ y_k \\ y_k \end{matrix} \qquad (10)$$

c) **Coordinated turn model:** Describes a steady-state manoeuvre with constant turn rate.

$$\begin{matrix} x_{k+1} \\ x_{k+1} \\ y_{k+1} \\ y_{k+1} \\ y_{k+1} \\ y_{k+1} \end{matrix} = \begin{matrix} 1 & \frac{\sin(wT)}{w} & 0 & \frac{-(1-\cos(wT))}{w} & 0 & 0 \\ 0 & \cos(wT) & 0 & \sin(wT) & 0 & 0 \\ 0 & \frac{(1-\cos(wT))}{w} & 1 & \frac{\sin(wT)}{w} & 0 & 0 \\ 0 & \sin(wT) & 0 & \cos(wT) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{matrix} \quad \begin{matrix} x_k \\ x_k \\ y_k \\ y_k \\ y_k \\ y_k \end{matrix} \qquad (11)$$

III. USING AIS MESSAGE

AIS message type 1, 2, 3, 4 and 17 provide position information of surface contacts fitted with AIS transponder. Reference [7] provides with standard AIS message decoding logic, which is used in order to decode position reports of mobile AIS transponders on ships which can be used along with radar plots at data association stage in To-MHT for improving track maintenance. The absolute position converted to cartesian coordinates with reference to radar's own position is used along with speed and course information in the implementation which is explained in next section.

IV. IMPLEMENTATION

This implementation assumes that tracks are already initiated with an independent track initiation algorithm. The input to proposed track maintenance module include IMM Kalman filter data structure for each target initialized with state transition matrices for 3 models described by equations (9), (10) and (11) along with process noise covariance and measurement noise covariance as described in [3]. This track maintenance module will run in loop with each run utilizing current scan plot (measurement) data and decoded AIS information. The flow chart of proposed implementation is shown in Fig 3.

V. SIMULATION AND EXPERIMENTAL RESULTS

Scenario of 5 closely moving targets:

In the simulation, 5 closely moving targets (with separation distance just above radar azimuth resolution i.e. typically less than or equal to 500mts as shown in Fig 2) are considered moving at constant velocity for 100 scan intervals. At the end of 60th scan interval each target is made to manoeuver with an arbitrary rate of turn omega, which is chosen in interval (-5 deg to +5 deg). Uniformly distributed clutter with clutter density of 1e-07 is introduced in the overall simulation area and number of clutter points in each scan interval follows poisson distribution. During track maintenance, the validation gates of these targets overlap thus giving rise to ambiguity in track to measurement association in each scan.

A typical track tree expansion scenario is shown in Fig 4. The resulting state estimate of tracks obtained from Track-oriented MHT process described in this paper is shown in Fig 5. Fig 6 shows average number of measurements falling within validation region of each track during Monte-Carlo runs.

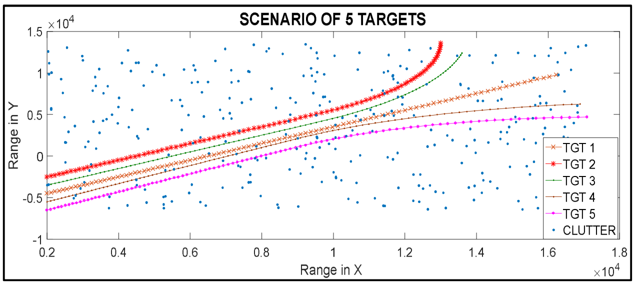

Fig (2): Scenario of five closely moving targets.

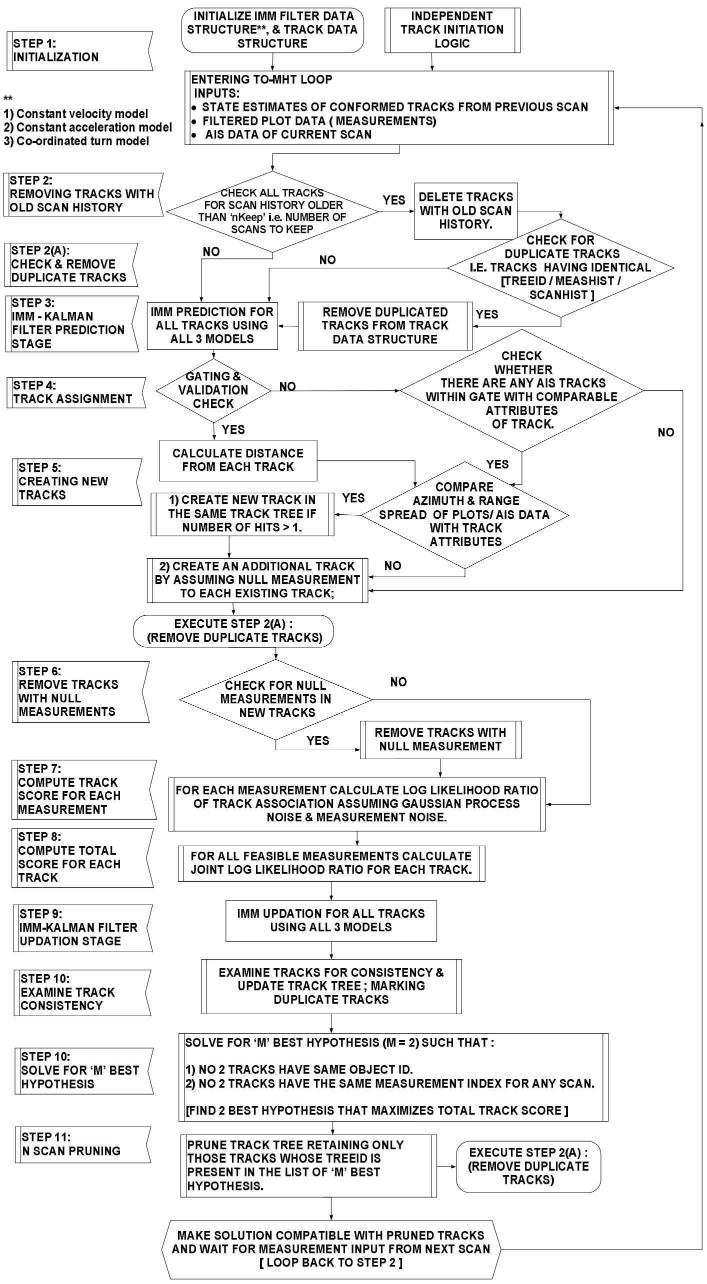

Fig 3: High level block diagram of track oriented MHT with IMM Kalman filter using AIS data.

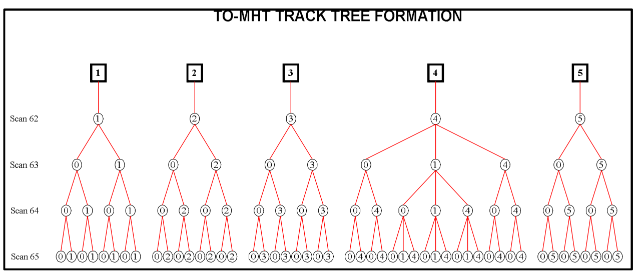

Fig (4): Typical track tree formation process for 5 target scenario.

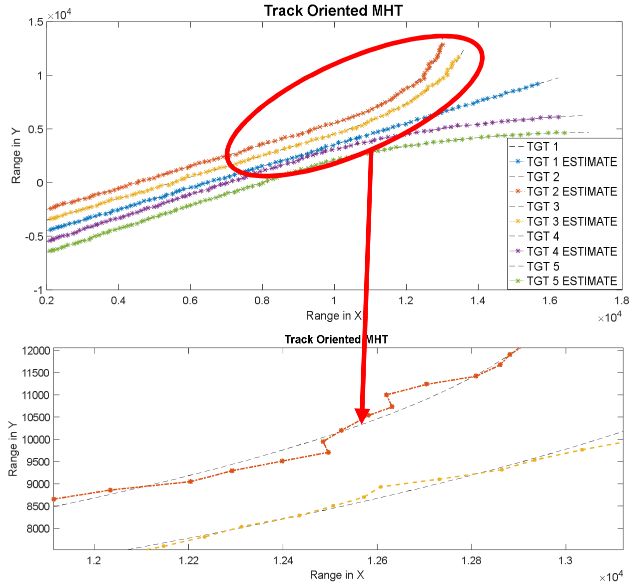

Fig (5): TO-MHT estimates for 5 closely moving targets scenario with gate (g = 5 sigma) & clutter density =1.5e-7.

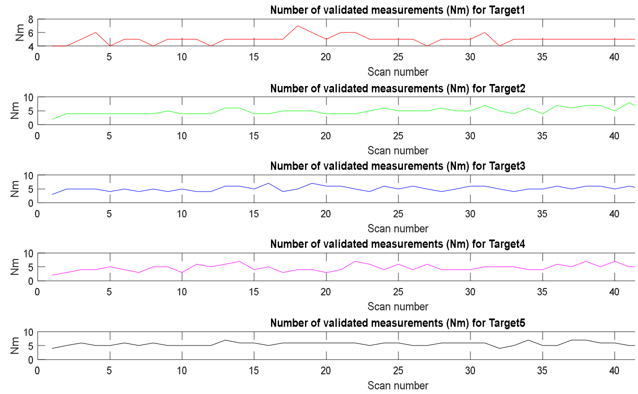

Fig (6): Average number of measurements falling within gate for each target in each scan for 50 Monte-Carlo simulation runs with gate (g = 5 sigma).

Table 1: **Comparison of performance of GNN, JPDA, MHT (hypotheses oriented) and TO-MHT for 5 closely moving target scenario.**

METHOD	Average error in estimates for 100 scans (clutter density = 1e-7)				Time (sec)
	err-x	err-y	err-x_v	err-y_v	
HO-MHT (Targets 1-5)	41.01	49.31	16.59	16.53	30.08
	43.61	42.49	15.14	14.86	
	62.02	51.93	18.56	17.69	
	42.58	60.73	15.66	15.99	
	51.91	72.47	16.13	19.78	
Proposed method (Targets 1-5)	33.80	34.33	7.84	7.72	11.66
	36.81	41.40	8.16	8.37	
	36.44	39.75	8.06	8.33	
	40.07	35.70	8.35	8.02	
	36.98	38.31	8.01	7.85	

Scenario of manoeuvring target:

In the simulation, a single manoeuvring target is considered moving at constant velocity for 100 scan intervals as shown in Fig 7. The rate of turn omega, is chosen in interval (-30 deg to +30 deg) in between scan number 30 to 70. Uniformly distributed clutter with clutter density of 1e-07 is introduced in the overall simulation area and number of clutter points in each scan interval follows poisson distribution. During track maintenance, the IMM Kalman filter estimates for all 3 models are weighted and a composite track estimate is formed as shown in Fig 8. **Table 2** shows results of 50 Monte-Carlo simulation runs.

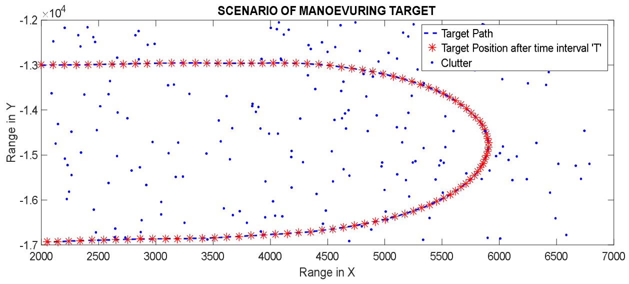

Fig (7): Scenario of manoeuvring targets.

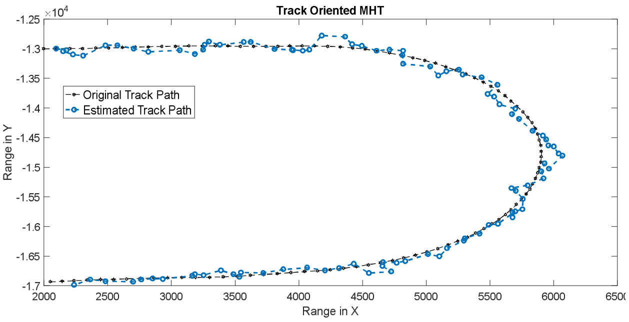

Fig (8): IMM based TO-MHT estimated track for scenario shown in Fig (5).

Table 2: **Comparison of performance of GNN, JPDA, MHT (hypotheses oriented) and TO-MHT for single manoeuvring target scenario.**

METHOD	Average error in estimates for 100 scans (clutter density = 1e-7)				Time (sec)
	err-x	err-y	err-x_v	err-y_v	
HO-MHT (Targets 1-5)	41.01	49.31	16.59	16.53	30.08
	43.61	42.49	15.14	14.86	
	62.02	51.93	18.56	17.69	
	42.58	60.73	15.66	15.99	
	51.91	72.47	16.13	19.78	
Proposed method (Targets 1-5)	33.80	34.33	7.84	7.72	11.66
	36.81	41.40	8.16	8.37	
	36.44	39.75	8.06	8.33	
	40.07	35.70	8.35	8.02	
	36.98	38.31	8.01	7.85	

VI. CONCLUSION

The proposed method in this paper provides an efficient multi-target track maintenance method useful for tracking surface targets in sea from a shore based radar. The use of IMM Kalman filters improves efficiency of this algorithm for tracking target manoeuvres. The use of AIS information improves track maintenance in situations when detection probability is less. Further work will involve integration of track initiation with the proposed approach.

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BIOGRAPHY

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Dr. A A Bazil Raj is working as assistant professor at Defence Institute of Advance Technology, Pune. His research activities include Radar/Optical Signal Processing, Free Space Optical Communication, Empirical modelling, VLSI (SoC/NoC) design. He has 14 years of academic experience and has more than 40 publications. He has authored 3 books on free space optical communication.