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A Neural Network Target Tracking Using Kalman Filter

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ABSTRACT:

The power range and speed of weapon have increased exponentially during 50 plus years. The greater the range of weapon and target, the greater the problem of locating the target. The existing tracking filters are accurately needed for Fire Control Systems (FCS) and hence the coupling of Neural Network with kalman tracking filters to reduce the error in the target parameters.

In anti – submarine warfare, target motion is analyzed to track down the target. The sonar in the own ship generates the bearing information with the help of which it is possible to estimate the target data using tracking filter. In this we are using matlab simulation is implemented.

KeyWords: FCS,hydro acoustic signal matlab, Neural Network, tracking filters.

1. INTRODUCTION

Basically there are two types of sonar's.

1.1ACTIVE SONAR :-

Active sonar is a device for establishing the presence and determining the properties of underwater objects based on injecting hydro acoustic signal in to the water and then receiving and processing the received echo signals arising when their sound waves are reflected by underwater objects.

1.2 Passive sonar :-

Passive sonar is a device for establishing the presence and determining the properties of underwater objects through the reception and processing of acoustic signal emitted by these objects.

In the simulation study, typical geometrics of observer and target paths are assumed and a sensor signal simulator is designed to simulate the passive sensor information and to have target simulated parameters. But in real life situation the signal emanated from the sonar, is disturbed by the environment. In order to mimic this situation, the simulated bearing is contaminated with Gaussian noise by adding the Gaussian random numbers generated with zero mean and standard deviation 0.25 degrees. The bearing information added with the Gaussian noise, called the measuring bearing, is fed to the passive target tracking filter called kalman filter.

The kalman filter estimates the target parameters namely range,course,velocity and bearing. The input to the filter are the measured bearing a covariance matrix, the sample time and an intial state vector. The target parameters estimated by the filter are checked for errors with already simulated parameters. Percentage of error is then computed. Low percentage of errors is desired. But it has been observed that errors are not satisfactory. In order to, further reduce the errors; the kalman filter is coupled with the artificial neural network.

Neural Network is a biological inspired technique which can compute any military applications. An important property of N.N is that, whatever they can compute they can LEARN to compute. So, a multilayer feed forward B.P.N.N is chosen and is trained for different observer target geometries. The input to the network is the kalman gain, predicted state vector minus estimated state vector and predicted state vector.

The trained network is coupled with the filter to estimate the parameters again. From the results it is concluded that the network aided filter produced considerably low errors when compared with those of the parameters estimated by the filter alone.

Simualtion is a method used to study the dynamic of the system. The approach can be used to study almost any problem. It requires a model to be constructed that represents the systems behavior in terms of mathematical and logical relationship between the variables. This model should represent the primary effects that relate to the problem being studied.

Each simulation run is essentially an experiment on the system. The advantage is that these experiments can be completely controlled and completely observed. Simulation is not used to replace mathematical analysis; instead mathematical analysis is used to replace simulation to as great a degree as possible.

The primary reason for using simulation is that many models cannot be adequately analyzed by standard mathematical techniques. It is applicability. Simulation does not necessarily involve computers. But the availability of these devices helped to extend the application of simulation to many new areas.

However, it is very difficult to draw accurate conclusions from simulation studies. The difficulties are due to problems associated with both developing an effective model and drawing meaningful conclusions from simulation results.

The model developed for this particular simulation study is the "SENSOR SIGANL SIMULATOR". The sensor or sonar generates bearing for different assumed positions of the observer and target. Bearing is the angle measured with respect to true North.

1.3 THE SENSOR SIGNAL SIMULATOR IS DEVELOPED AS GIVEN BELOW :

The acceleration of anybody moving with uniform velocity is zero.

The velocity can be divided in to 2 components: $V\cos\theta$ – along X direction, $V\sin\theta$ – along Y direction

The range along X and Y direction are calculated for both observer and target. With help of these values the bearing is measured using the formula with respect to north axis(y- axis).

Bearing $B = \tan^{-1} [(X_t – X_0) / (Y_t - Y_0)]$

Where X_t ,Y_t are the target position along X and Y directions

X_0,Y_0 are the observer position along X and Y directions.

The target can approach the observer from any angle between 0^0 and 360^0

Considering this scenario on the XY plane, we can divide the plane in to four quadrants and update the bearing depending upon the presence of the target in that quadrant. The updating formulae for bearing are as given below,

y-axis is north & x-axis is east.

Bearing = B + 0 in quadrant I

Bearing = 360 – B in quadrant II

Bearing = 180 + B in quadrant III

Bearing = 180 – B in quadrant IV

2. AN OVERVIEW OF KALMAN FILTER

Much of the early impetus for the development of kalman filter theory and appilications came from problems in the aerospace industry. The state variables in such appilications are position and velocity. The basic task is to estimate, as accurately as possible, the position and velocities of the moving object from radar noisy measurements of range and bearing. The moving object could be a ship, aircraft or submarine or it could be a whale or fish. The measuring equipment involves the sensors like radar, sonar or optical sensor. In order to keep the problem within manageable proportions, this work restricts attention to only two-dimensional cases. These kinds of problems are called target/contact motion analysis problems or tracking algorithms. The coordinate selection associated with the state vector variables will play a key role in KF divering/ converging cases.

The statistical characteristics of the noise depend, to a large extent, on the measurement equipment. It is observed that the KF is optimum only for the case of Gaussian noise. The KF is an unbiased, stable and optimal estimator with minimum variance, if the system is stochastically controllable and observable, while some noise assumptions are satisfied. Because of its real time limitations, the tracking filter traditionally adopts a target model with constant velocity motion.

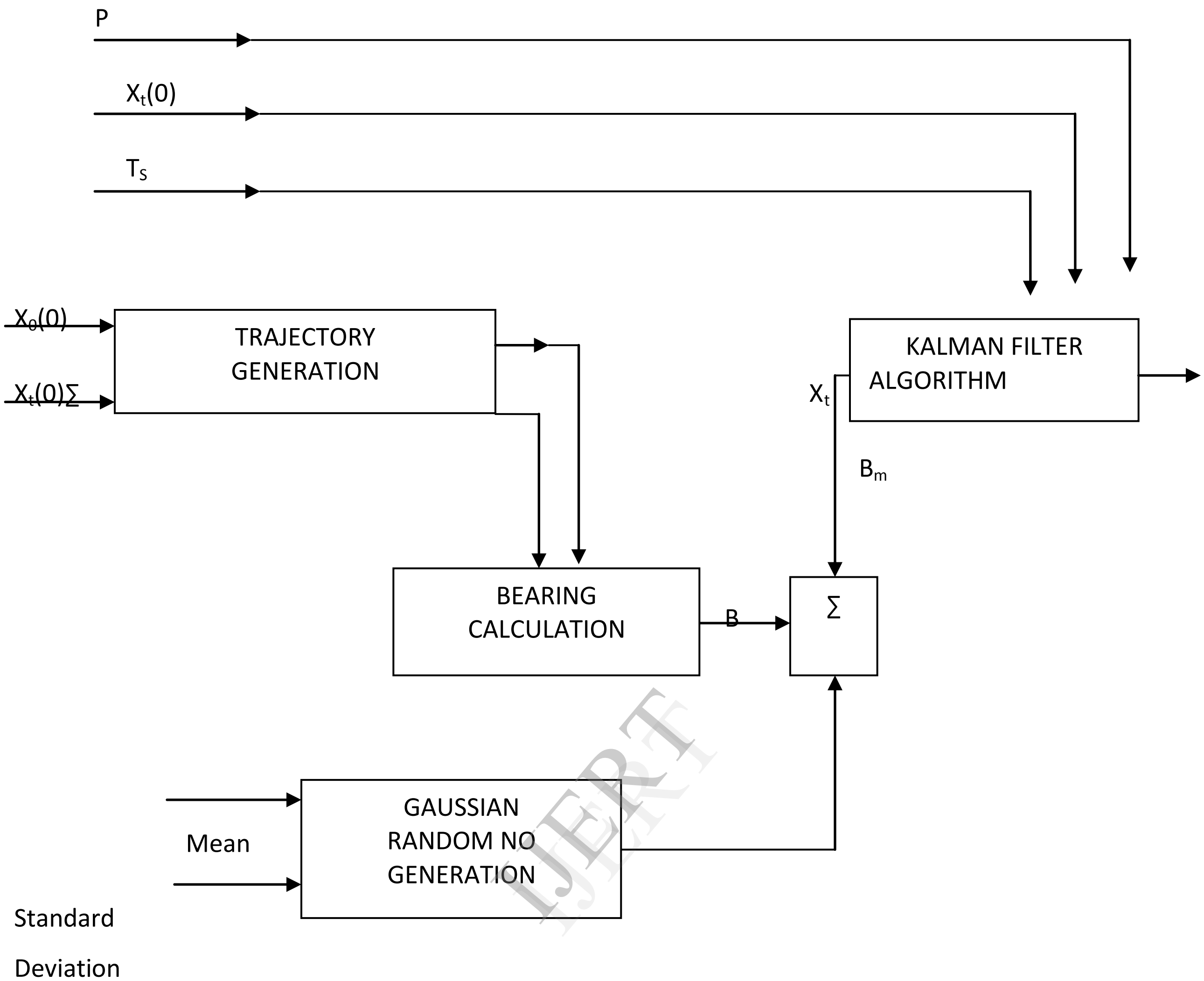
The demands of high precision tracking and guidance system for future tactical/ strategically system require accurate target state estimation. A variety of target tracking algorithms have been in the literature for this kind of problem, namely, least square algorithm, maximum likelihood estimate and KF and its derivatives. When the target model is changed, to account for maneuvering dynamics of target, these above mentioned methods fail to produce accurate results, resulting to go for novel schemes, such as neural and fuzzy solutions to the target estimate. The KF is very much sensitive to measurement noise and disturbances. A number of adaptive filters have come with not much impact.[i]

The KF assumes the availability of a state model and an observation model. The system state model represents the dynamics of observer and target to be tracked and it is best described in a rectangular coordinate system. On the other hand, the observation model is determined by sensor system. The status of these models is estimated by linearising non-linear model. Linearisation errors may, in some cases, force state estimate prone to divergence. State estimation with the KF coupled with neural nets is accomplished to reduce the tracking errors. The performance of this new approach is compared with the old approach. Hence, the proposed scheme allows one to model a target motion accurately, which leads to better target motion accurately, which leads to better target tracking then tracking with only KF.

The KF is a linear, discrete-time, finite-dimensional, sequential, recursive system. The input of the filter is sensor information contaminated with noise, whereas the output of the KF is the target parameters. Obviously, the state vector depends on the particular sensor information being processed. In KF algorithm, error covariance matrix: ECM has been computed. Normally, the covariance matrix is both, a conditional ECM associated with the state estimate and an unconditional ECM associated with the filter estimate; it can be pre computed as the filter gain matrix. The KF equations require the evolution of the Gaussian conditional probability density of the state.

Because of the dependence of measurement matrix 'H' on the actual system measurements, gain cannot be computed apriori. Since ECM is no longer independent of measurements, it loses interpretation as an unconditional ECM of the estimator, though it is still conditional ECM.

A number of real world problems that have been successfully solved using KF theory are mentioned here. These filters have been used in the estimation of chemical process elements at various stages; in filtering from two-dimensional images; in civil engineering applications (stream flow model prediction) ; in communication system (demodulation of frequency modulated signals).



P – COVARIANCE MATRIX.

Xt – TARGET STATE VECTOR

XO OBSERVER STATE VECTOR

B – ACTUAL BEARING

Bm – MEASURED BEARING.

The block diagram of the Kalman Filter (KF) is shown here. KF filters noise from the signal contaminated with noise. The KF algorithm involves a series of matrix operations. Because of its recursive nature, it is suited to real time applications, State vector (X) is a 4 x 1 matrix.

$$X = [Rx, Ry, Vx, Vy]^T$$

Where Rx and Ry are ranges in x and y directions and Vx and Vy are relative velocities in the x and y directions. This state vector is the estimate of the target position .

The initial state vector, X =$[P0\ Q0\ O0]^T$

Where pO and qO are the x and y coordinates of the approximate target position.

Error Covariance Matrix (ECM) is a measure of the error in the estimation of the state vector. It is a 4 x 4 matrix. When the estimated target parameters approach the simulated values, the non-diagonal elements of the ECM must approach zero. This matrix has been initialized to identity matrix of t order 4 x 4.

The transition matrix is a 4 x 4 matrix,which is initialized to

Where T is sampling time. O is a constant and does not change with time.

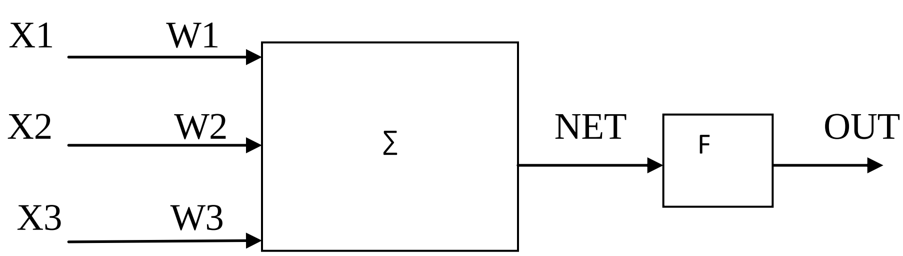
3.ARTIFICIAL NEURAL NETWORK CONCEPT

Artificial Neural Network is an advanced simulation technique incorporating ideas from many fields from neurobiology to psychology and philosophy to engineering and capitalizing on modern day parallel processing and microelectronics capabilities.

AAN is biologically inspired and is composed of elements that perform in a manner analogue to the elementary function of the biological neuron.

3.1 MATHEMATICAL MODEL OF AN ARTIFICIAL NEURON:-

The structure of the artificial neuron consists of receiving sites (synapses) receiving connections (dendrites) ; a processing element (cell body) ; and transmitting connection (axon). This architecture provides the path for the flow of data.



Each neuron is given a set of inputs. The inputs are multiplied with corresponding weights and the sum of the products is NET.

NET=Xo Wo+X1 W1+……Xn Wn

Where, X1=are input values and

W1=corresponding weights, for i=1ton

The net signal is processed by an activation function 'F' to produce the nueron's output signal, OUT.

OUT=F(NET)

The activation function is chosen to be a sigmoid logistic function, also called as squashing function. $F=1/(1+e^{-x})$

$OUT=1/(1+e^{-NET})$

This is an 'S' shaped function whose value range from 0 to 1.the function compresses the range of net ,so that out never exceeds some low value regarding of the value of net.

Other activation function that can be used is OUT = tanh (NET). It is also 'S' shaped but symmetrical about the origin and assumes bipolar values (-1 to1)

3.2 IMPLEMENTATION OF KALMAN FILTER:-

The KF algorithm involves the computation of both predicted and estimated state vector and predicted ECM, apart from kalman gain.

Measurement matrix 'H' is a 1*4 matrix.

This matrix depends on the bearing information from the sensor.

H= [cos B- sin B 0 0]

The predicted state vector and predicted ECM use previously estimated state vector and ECM respectively, except in the initial case.

X (k+1/k) = Φ (k+1/k)* X(k/k)

PREDICTED ECM:

P(k+1/k) = Φ (k+1/k) *P (k/k) *ΦT(k+1/k)

KALMAN GAIN MATRIX:

K(k+1/k)=P(k+1/k)*H^T(k+1)*[H(k+1)*P(k+1/k)*H^T(k+1)+1]^-1

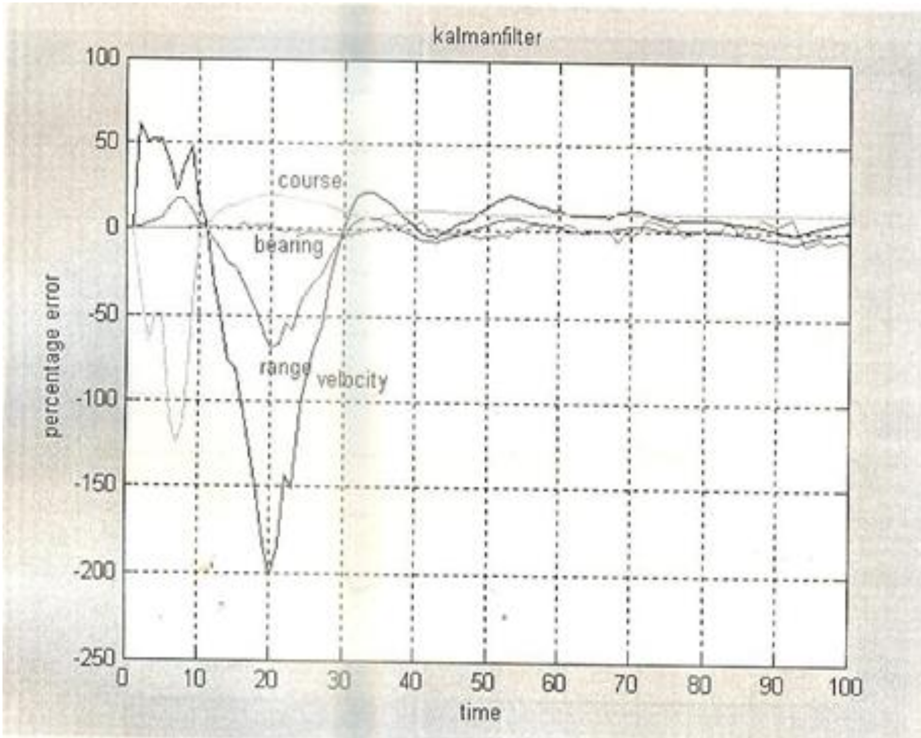
ESTIMATED STATE VECTOR:

X(k+1/k) = X(k+1/k)-K(k+1) * H(k+1)* X(k+1/k)

4. SIMULATION, RESULTS AND PLOTS

Six typical geometrics of the observer and target are simulated in all 360^0. And the target parameters like velocity, range, bearing, course, are calculated. These geometers are shown in Appendix1, in fig1. The target course is 90^0 and observer moving at origin. Like wise all geometers are shown in appendix1.

For the first geometry the velocities 4,16m/s are taken respectively for observer and target. And course of target is taken as 90^0. The parameters have shown maximum diversity after 20 samples. From 30 samples the parameters are converging. The Neural network has reduced further errors. The parameters have maximum diversion after 25 samples. After that they are more converging than kalman filter. Remaining 3 geometry also generated.



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