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State Estimation Using Neural Networks

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Abstract: In underwater scenario, tracking i.e. computing motion parameters of targets is a challenging task. In this field Sonars act as sensors which provide directional or approximate positional measurements of static/moving targets in Polar coordinate system which makes the system parameters nonlinearly related with measurements. The prevalent solutions available in literature like EKF, UKF and PF approximate the relation through linearization etc. Artificial Neural Networks (ANN) is famous as nonlinear model free data driven estimators. They were applied with striking success in the field of control systems (System Identification), Speech processing (Noise cancellation) etc. The present work is a novel effort to apply ANN to handle nonlinearity and to improve tracking accuracy. Performance of proposed algorithm is compared with existing tracking algorithms EKF.

Keywords: Target Tracking, State Estimation, Neural networks, Maneuver

I. INTRODUCTION TO UNDER WATER TARGET TRACKING

In this work, objective is to improve underwater target tracking using range and bearing measurements of a target computed by active sonar. In underwater scenario, sonars fitted onboard ships and submarines seek target localization by pumping acoustic energy into the water. Active sonar processes the reflected acoustic energy from target surface and determines an estimate of target range and bearing. These estimates are dependent on target type, sea state and many other environmental parameters existing on that day. Estimation of target velocity vector is done by advanced tracking algorithms like Extended Kalman Filter, UKF, etc.

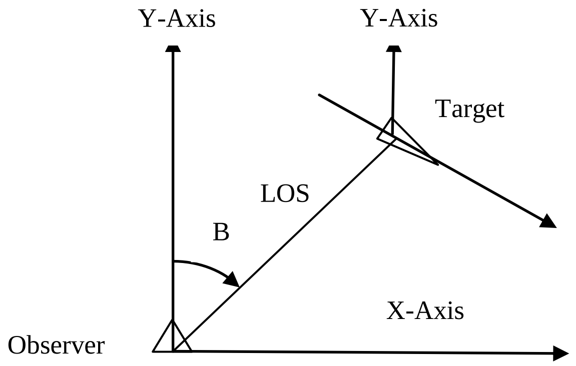

FIG1. TARGET AND OBSERVER ENCOUNTER.

Target tracking is the process of computing target motion parameters (TMP) of a moving/stationary target. TMP are all kinematic parameters of the target that completely define its motion at any given moment. TMP for moving target are range, bearing, course speed, acceleration, turn rate etc. The number of parameters and their values depend on the type of kinematics in vogue at a given time.

The generic problem of target tracking can be broadly classified into two distinct classes – tracking a maneuvering target and tracking a non-maneuvering target. Tracking a non-maneuvering target has been historically a well discussed problem and has been mainly solved by using Kalman Filter (KF) and its variants.

TABLE1. TARGET TRACKING TERMINOLOGY

Term		Description	Units
LOS	Line of Sight	An imaginary line joining Observer and Target	
B	Bearing	Angle made by LOS with Y-Axis	Degrees
R	Range	Length of LOS	Meters
C	Target Course	Angle made by target velocity vector with respect to Y-Axis	Degrees
S	Target Speed		Knots
OC	Observer Course	Angle made by observer velocity vector with respect to Y-Axis	Degrees
OS	Observer Speed		Knots

The key to successful target tracking lies in the effective extraction of useful information about the target's state from observations and a good model of the target will facilitate this information extraction process to a great extent. In the field of underwater target tracking where only 2-D target motion analysis is done, estimation can be defined as the process of inferring values of four parameters of motion i.e. 2 position and 2 velocity parameters ($\dot{x}$, $\dot{y}$, R_x, and R_y)- evolving in a predictable/unpredictable manner.

II. MODELING EQUATIONS

Almost all target tracking methods are model based and assume that target motion and its observations can be represented by known mathematical models sufficiently accurately in the following form:

$$X(k+1) = \emptyset(X(k), u(k+1)) + w(k) \qquad (1)$$

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$$Z(k) = H(X(k)) + v(k) \qquad (2)$$

Equation (1) is called state equation and (2) is called measurement equation. The target state vector is X(k), where

$$X(k) = [\dot{x}(k) \quad \dot{y}(k) \quad R_x(k) \quad R_y(k)]^T \qquad (3)$$

$\dot{x}(k)$and $\dot{y}(k)$ are target velocity components, and $R_x(k) = R\sin(B)$,$R_y(k) = R\cos(B)$ are range components along x and y axes respectively. System state evolves over time 'k' and discrete time state equivalent of dynamic equation (1) modelled as Marcov process is given by:

$$X(k+1) = \emptyset\left(k+1/_k\right)X(k) + B(k+1)\,u(k+1) + w(k) \qquad (4)$$

Where $\emptyset$ and B are transition and system input gain matrices respectively. u is the input to the system to be controlled or whose state is to be estimated. w(k) is assumed to be the additive white Gaussian noise for realizing un-modelled system dynamics. Measurements observed from the system are a function of the current state of the system. Discrete time equivalent form of (2) is given as

$$Z(k) = H(k)X(k) + v(k) \qquad (5)$$

In 2D applications, $Z(k)$ constitutes only bearing (azimuth), and range information of the target. The bearing measurement $B_m(k)$ and range measurement $R_m(k)$ are modelled as

$$B_m(k) = tan^{-1}\left(\frac{R_x(k)}{R_y(k)}\right) + v_b(k) \qquad (6)$$

$$R_m(k) = \sqrt{R_x(k)^2 + R_y(k)^2} + v_r(k) \qquad (7)$$

Where $v_b(k)$ and $v_r(k)$ are errors in the bearing and range measurements respectively with errors assumed to be zero mean Gaussian with variances σ_b and σ_r respectively. The measurement and plant noises are assumed to be uncorrelated.

III. CHALLENGES IN TARGET TRACKING

A. Linearity and Non linearity:

Mathematical Models represented by equations (1) & (2) are nonlinear-continuous and (4) & (5) are their linear-discrete counterparts. Most of the problems of estimation have their models in a nonlinear form. Existing nonlinear estimation methods find approximate solutions by Taylor series linearization, Sigma points and probabilistic particles approach as no direct methods exist. If target is moving with Constant Velocity (CV) or with Constant Acceleration (CA), state model relation $\emptyset$ is straight forward and if it is turning with fixed rate 'ω' but with constant speed, $\emptyset\left(k+1/_k\right)$ can be derived as

$$\emptyset\left(k+1/_k\right) = \begin{bmatrix} cos(\omega t) & sin(\omega t) & 0 & 0 \\ -sin(\omega t) & cos(\omega t) & 0 & 0 \\ \frac{sin(\omega t)}{\omega} & \frac{1-cos(\omega t)}{\omega} & 1 & 0 \\ -\frac{1-cos(\omega t)}{\omega} & \frac{sin(\omega t)}{\omega} & 0 & 1 \end{bmatrix} \qquad (8)$$

In the above case, $\emptyset\left(k+1/_k\right)$ is linear only if turn rate ω is assumed to be fixed. Otherwise ω will be a parameter in state vector $X(k)$ to be estimated which makes the relation $\emptyset\left(k+1/_k\right)$ nonlinear in 'ω'. The relation between current state and the measurements $Z(k+1)$ is given by the equation (2). The relation $H(:)$ depends on the chosen coordinates system for state vector $X(k)$ and measurements $Z(k)$. Implications of choice of coordinate system for tracking a straight moving target are given below:

Sl. No	**Coordinate system**		**Result**	
	State	**Measurement**	**State Eq.**	**Measure ment Eq.**
1	Cartesian	Cartesian	Linear	Linear
2	Cartesian	Polar	Linear	Non-linear
3	Polar	Cartesian	Non-linear	Non-linear
4	Polar	Polar	Non-linear	Linear

Table2. Linearity vs. Coordinate System Choice of Coordinate System

As measurements form sonar are polar, only Sl.No 2, 4 are practically real situations. As a result, there exists non-linearity in either state or measurement equation. Apart from the above cases if the target maneuvers, nonlinearity may occur in state equations. Also approximation of models induces Non stationary, Non Gaussian and Correlated noise.

B. Maneuvering Target Tracking

Maneuvering Target: In most realistic situations, all platforms in underwater move in straight path and change their course and speed very rarely. Kinematics of such vehicles can be modeled to be of CV. However assuming CV model is not always valid as it is not sufficient to track the target during maneuver. Maneuvering target tracking methods [2] available in literature handle State equation given by (1) in different ways.

1) Maneuver Modelling using $\emptyset\left(k+1/_k\right)$ **:** $\emptyset\left(k+1/_k\right)$ defines the evolution of state w.r.t time. Structure of $\emptyset\left(k+1/_k\right)$ remains same for any value of 'k'. Standard models like CV, CA, Constant Jerk (CJ), and Coordinated Turn (CT) are modelled easily. In actual applications, targets are bound to change their regime of maneuver and its sojourn time. Hence tracking methods like IMM (Interacting Multiple Model) run bank of parallel-cooperating filters with each filter having a different model.

2) Maneuver Modelling using $u(k+1)$: Maneuvers can be manifested in the form of external inputs that change one or all state vector components for a given duration of time. These inputs are available in navigation and not in military applications. Methods are reported in literature which consider these inputs as additional state variables to be estimated.

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3) Maneuver Modelling using (k) : No matter how accurately one selects the model, there is always a chance of mismatch in selected model and actual one due to physical limitations. Such minor differences in system dynamics are addressed by the process noise $\omega(k)$.

IV. EXISTING METHODS FOR TARGET TRACKING

A. Least Squares (LS)
Least Squares [5] is a parameter estimation method. The quantities to be estimated do not change with time. if the target is assumed to be moving with constant velocity and if the measurement $Z(k)$ at any given value of k is dependent on $H(k)$ and current state $X(k)$ then $Z(k) = H(k)X(k) + v$. Then the estimate of $X(1)$ i.e. $\hat{X}(1)$, can be estimated using LS approach as

$$\hat{X}(1) = \left(\hat{H}^T\ \hat{H}\right)^{-1} \hat{H}^T\, \hat{Z} \qquad (9)$$

Here $\hat{Z} = \begin{bmatrix} Z(1) \\ Z(2) \\ \vdots \\ Z(n) \end{bmatrix}$ and $\hat{H} = \begin{bmatrix} H(1) \\ H(2) \\ \vdots \\ H(n) \end{bmatrix}$ where $H(k) =$

$$\begin{bmatrix} sin(B_m(k)) & cos(B_m(k)) \\ cos(B_m(k)) & -sin(B_m(k)) \\ k\ \Delta t\ sin(B_m(k)) & k\ \Delta t\ cos(B_m(k)) \\ k\ \Delta t\ cos(B_m(k)) & -k\ \Delta t\ sin(B_m(k)) \end{bmatrix}^T$$

for $k = 1,2,3, \ldots n$.

B. Kalman Filter Based Algorithm

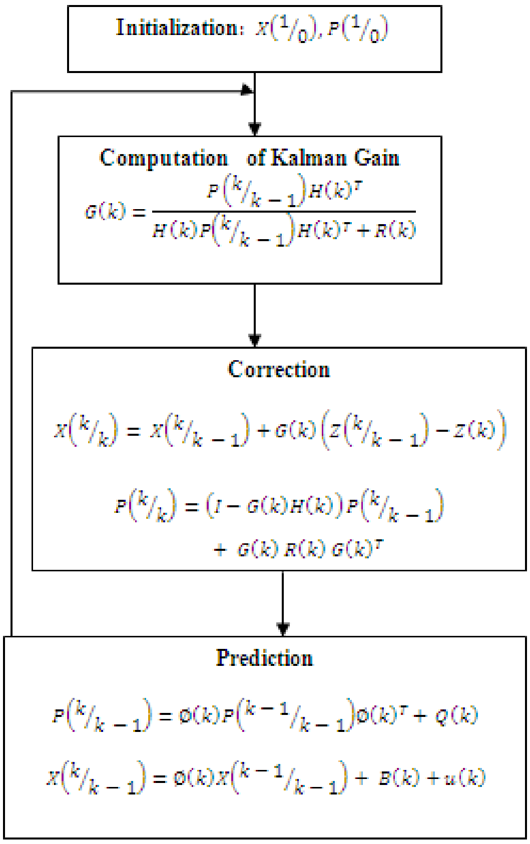

Fig.2. Kalman Filter Steps

KF [4], [6] is a well known estimator defined as recursive predictor-corrector based best linear unbiased estimator. It combines all available information plus prior knowledge about the system, measuring devices to provide an estimate of desired variables in such a manner that the error is minimized statistically. The main concept of this estimator is to minimize the means of square of error unlike LS which minimizes the measurement error.

KF can be applied to only linear systems and its nonlinear extension is Extended Kalman Filter (EKF). EKF addresses the nonlinearity in equations (1) & (2) through Taylor series approximation up to first-order terms.

C. UKF & PF Based
UKF [5] is another method of approximating nonlinearity by computing state mean and its covariance through deterministically chosen sigma points. Enough literature shows that it has an advantage over EKF. PF takesthe probabilistic approach of choosing the points or particles through various sampling methods.

V. PROBLEMS WITH EXISTING METHODS

A. Least Squares
LS do not consider any statistical characteristics of measurement/system noise. Its estimate is optimal only for available set of measurements at hand and may not be optimal for another set of measurements with different noise sequence.

B. EKF
EKF just extends KF to nonlinear applications and takes the deterministic approach of linearizing (1) and (2) about the predicted state estimate $X\left(k+1/_{k}\right)$ for measurement equation and about corrected state $X\left(k/_{k}\right)$ for state equation. Linearization of equations sacrifice the uncorrelatedness of the stochastic processes and may also induce unexpected bias. It only considers the first two terms of the Taylor series and higher order terms are discarded. It assumes orthogonality, uncorrelatedness of noise in most of the equations.

VI. NEURAL NETWORKS

Neural networks are applied widely applied in different applications of both mathematical/numerical processing to cognistic/linguistic applications. They are well established model free nonlinear function estimators suitable for control systems, etc. Although research in the field of NN based state estimation is scarcely found in literature [7],[8], some scientists like Alexander G. Parlos, et.al exploited NN for adaptive state filtering [9].

VII. MOTIVATION

Nonlinearity in maneuvering target tracking is associated with unknown turn rate. Tracking a target making a coordinated turn with known & fixed turn rate with the help of EKF is quite simple. But its performance usually is initialization dependent. Good idea of system model, initial state vector, process noise and measurement noise will significantly improve the convergence time of EKF.

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On the other hand LS method is purely data dependent and requires no initialization or prior information. In a case where measurement noise is assumed to be very high and if the measurements are more accurate than indicated by measurement noise covariance matrix, EKF would take more time to converge to reasonably accurate estimate. However LS would give a better estimate as its estimate is only dependent on data at hand. Hence, for tracking a target with unknown but fixed turn rate and in the event of inconsistent information about measurement noise, an LS based approach to target tracking is more appropriate. Unfortunately LS based formulation is applicable only if it is possible to derive a linear relation specified as by equation (9). There exists no straight forward analytical approach for above stated problem and this paper presents a novel approach to approximate the nonlinearity in state equation using Neural Networks.

VIII. DESIGN

It is well established in literature that, NNs are effective for nonlinear function approximation. The function to be approximated in case of a target tracking problem is shown below. The vector Z is the batch of measurements received from k=1 to k= n. $Z_n = \begin{bmatrix} R_n sin(B_n) \\ R_n cos(B_n) \end{bmatrix}$

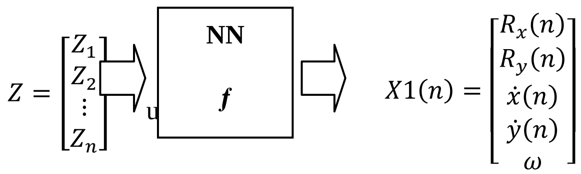

Fig3 Structure of NN Target Tracking Algorithm

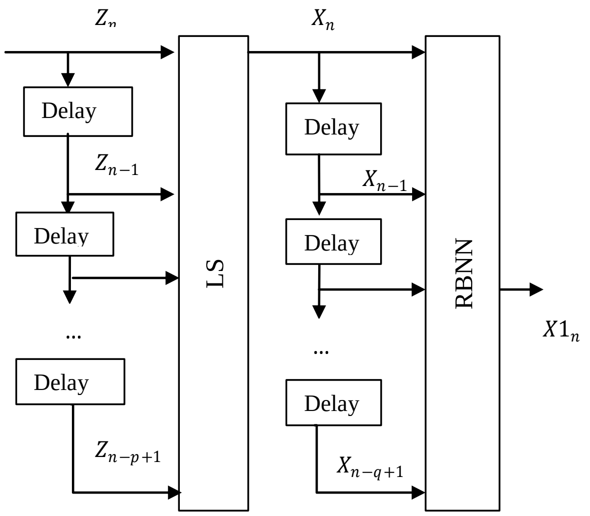

Fig. 3. Architecture of NN Based Algorithm

Measurements which are corrupted by noise are initially passed through a least squares tracking algorithm (LS) to filter out the noise. As an output of LS, we get the state estimates X_n to X_{n-q+1}. q Being number of inputs NN.

IX. DEVELOPMENT

Matlab Toolbox for Neural Networks provides good framework to select existing and design new NN models. API's for creating FFNN, RBNN, recurrent NN, NARX filters etc. with user flexibility to choose different learning functions are available directly as functions. Detailed documentation about NN tool box can be found on Matlab website. A FFNN with 3 layers (each of 5 neurons) was chosen to develop the proposed algorithm.

A. Software framework

As a part of design and verification of the proposed algorithm, a comprehensive software framework to simulate target kinematics, sonar track data and Monte-Carlo methods for comparing study are developed in MATLAB.

B. Training process

The training set is chosen based on the following values scenarios parameters.

Initial Range: 2 KM to 8 KM in steps of 500m
Initial Bearing: 0 to 360 degrees in steps of 30.
Initial Course: 0 to 360 degrees in steps of 30.
Initial Speed: 5 to 15 Knots in steps of 5.
Turn rate: 0 to 1 deg in steps of 0.1

X. RESULTS

The Comparative study (100Monte Carlo) with , EKF and proposed algorithm (FFNN) is done for the following noise and scenario specifications.

Noise Specs (1 sigma):
Bearing Noise is 0.5^0
Range Noise is 20m

Scenarios:

	Scenario1	**Scenario2**
R (Metres)	3000	3000
B (Deg.)	45	60
C (Deg.)	125	145
S (Knots)	15	10
Turn rate (Deg./sec)	0.5	0.3
OC (Deg.)	30	30
OS (Knots)	15	15

Table4. Scenarios Tested

Algorithms under Test

Algorithm	**Specifications**
RBNN	2000 Gaussian Functions
EKF	Noise Initialization: Range: Actual+20 m Bearing: Actual + 0.5 degrees

Table 3. Algorithms Under test and their specifications

Scenario1

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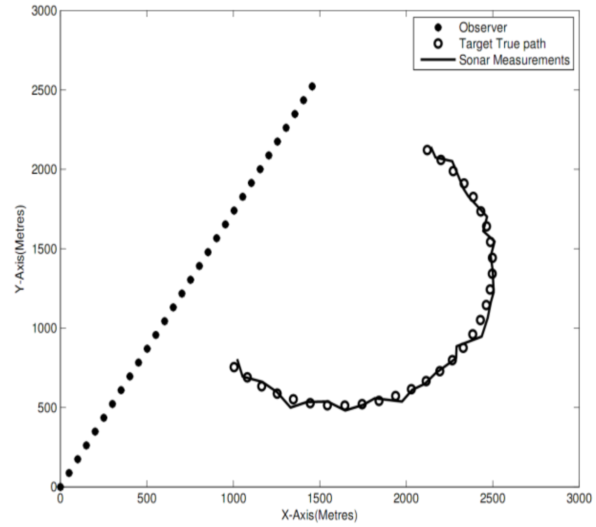

Fig4. Target moving as per scenario1

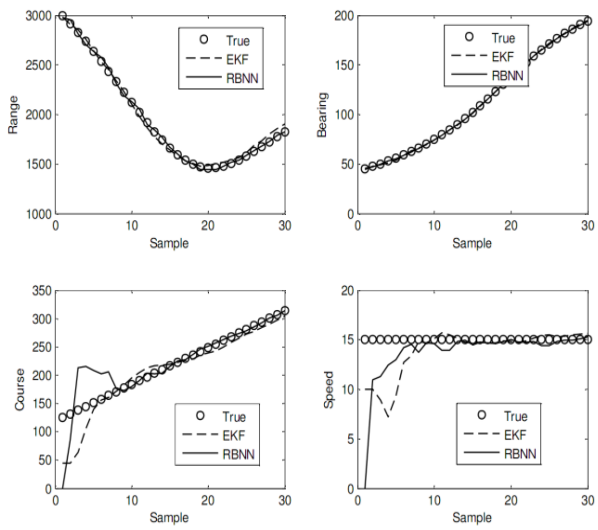

Fig5. Performance of RBNN for single run case

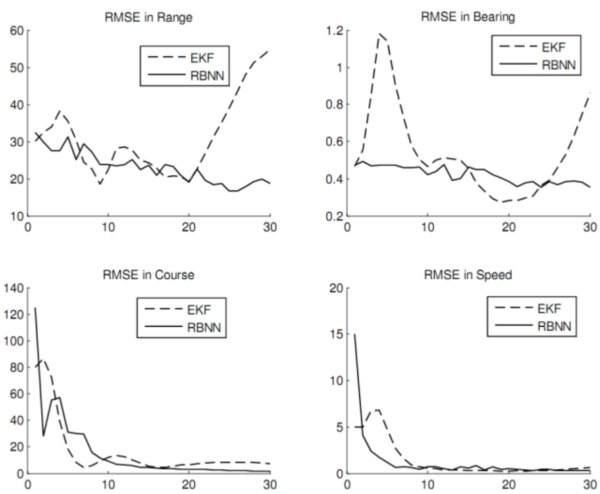

Fig6. RMSE error of RBNN algorithm

Scenario2

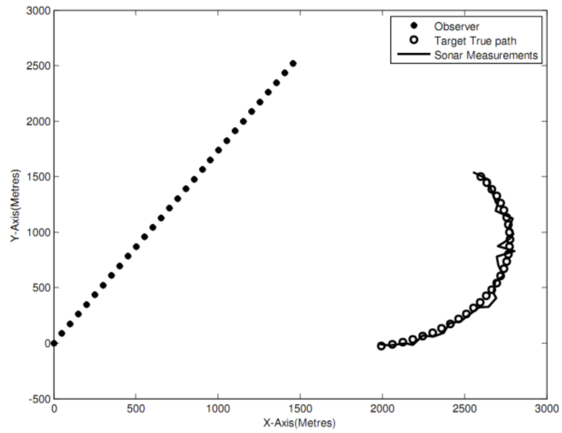

Fig7. Target moving as per scenario2

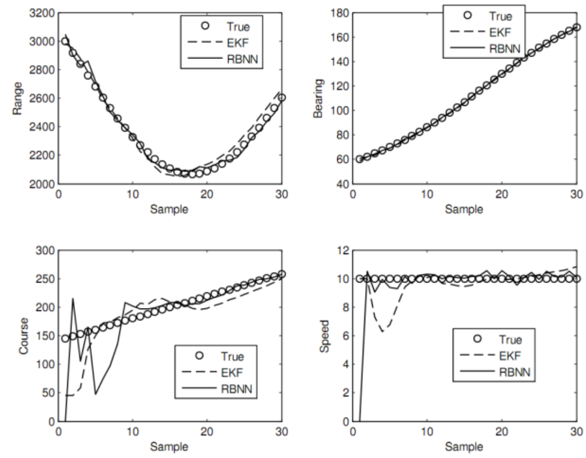

Fig8. Performance of RBNN algorithm for single run case

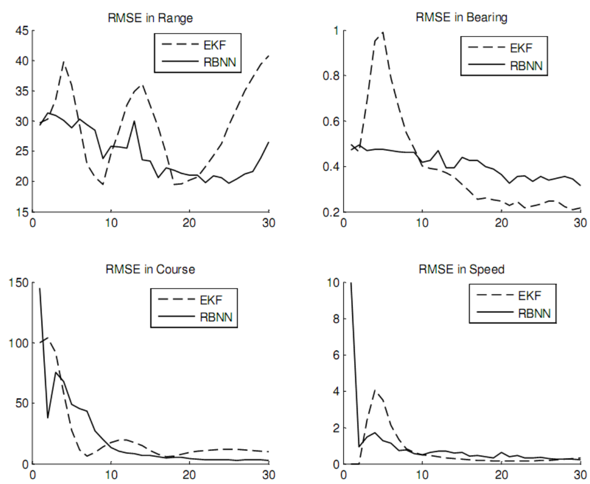

Fig9. RMSE error of RBNN algorithm

XI. CONCLUSION & FUTURE SCOPE

The proposed algorithm was developed using FFNN with 3 layers (each of 5 neurons). The whole algorithm was written in Matlab2010 as it has inbuilt functions for create NN and train them with well known algorithms like back propagation, Levenberg–Marquardt algorithm, etc.

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Performance of the algorithm has been verified with existing algorithm i.e. EKF. Performance of new algorithm was found to be better for tracking a target making a coordinated turn with unknown turn rate. Especially in a situation where the measurement noise is less and not exactly known.

For clarity of concept, the algorithm was developed only for 2D active target tracking. It assumes that the target does only single turn with fixed turn rate throughout the duration. The algorithm can be extended for 3D and for tracking using passive sonar measurements. The assumption of fixed turn rate can be relaxed by considering variable turn rate. But this increases number of training scenarios vis-à-vis training time for a static network. On the other hand due to its static nature, the weights of the network are fixed and cannot be changed online. By extending the algorithm to use a recurrent neural network, the need for processing batch of measurements can be prevented. While using a recurrent version makes it adaptive to lean in real time situation.

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BIOGRAPHY

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