Recurrent Neural Network Approaches for Nonlinear Filters of Navigation Systems

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Abstract: For vehicle integrated navigation systems, real-time estimating states of the dead reckoning (DR) unit is much more difficult than that of the other measuring sensors under the indefinite noises and nonlinear characteristics. Compared with the well known extended Kalman filter (EKF), *a recurrent neural network* is proposed for the solution, which not only *improves the location precision, the adaptive ability of resisting disturbances*, but also *avoids calculating the analytic derivation and Jacobian matrices* of the nonlinear system model. In order to test the performances of the recurrent neural network, these two methods are used to estimate states of the vehicle DR navigation system. Simulation results show the recurrent neural network is *superior to the EKF* and is *a more ideal filtering method* for vehicle DR navigation.

Key words: dead reckoning; extended Kalman filter; recurrent neural network; vehicle integrated navigation systems

1. Introduction

With the advantages of all weather, globality, and high precision, Global Position System (GPS) has been widely used in vehicle navigation system to provide the vehicle's position and velocity information[1].Unfortunately, the GPS signals are often screened or disturbed when the vehicles are in the urban canyon, tree-covered areas, or tunnels, which makes GPS receiver unable to work normally. At present, the popular supplemental system to improve GPS accuracy is dead reckoning system (DR), which can obtain the position of the vehicle through measuring outputs of the low-cost rate gyro and the odometer. GPS and DR have complementary characteristics. The smoothness and constant availability of the DR signals can be used to correct the errors of the GPS signals due to the noise effects and blockage problems, while the absolute position accuracy of GPS can be used to provide feedback signals to correct the dead reckoning. However, for the indefinite noises and the nonlinear characteristic, accurately estimating the states of the DR in the real world is much more difficult than that of the GPS.

During the past 20 years, the EKF has been widely applied to this problem. However, the model of the system used in state-estimation is assumed to be perfectly known, along with the statistics of the process and sensor noise entering the system. These assumptions severely restrict the application in real world. Furthermore, the EKF approach linearizes the nonlinear function through a truncated Taylor-series expansion at a single point[1,2], which is sub-optimal and can seriously affect the accuracy or even lead to divergence of the filter.

Due to this and the need for more accurate and theoretically better motivated algorithmic alternatives to the EKF, a recurrent neural network is proposed in this paper. In principle, the neural network method of solution appears similar to the EKF. However there are some significant differences: Firstly, the accurate analytic derivation and Jacobians of the nonlinear system, as in the EKF, are not required. Secondly, the noise statistics are assumed unknown and they are not explicitly needed in the filter computations. The recurrent neural network can not only approximate the functions of the nonlinear DR system, but also realize the state estimate in real time by using directly of the sensor measurements. In order to test the performance of the recurrent neural network to state-estimation for vehicle DR navigation system, a semi-physical simulation is implemented.

2. Problem Statement

In this section, the nonlinear model of vehicle DR navigation system is established and the general state-estimation problem is formulated.

2.1 The nonlinear model of vehicle DR system

The vehicle DR system is made up of the rate gyro and the odometer. The state vector and the measurement vector can be selected respectively as:

$$X(k)=\begin{bmatrix} e & v_e & a_e & n & v_n & a_n \end{bmatrix}^T,$$

$$Y(K)=\begin{bmatrix} \theta & s \end{bmatrix}^T \qquad (1)$$

where, e, v_e, a_e are the position, velocity and acceleration of the easting respectively; n, v_n, a_n are the position, velocity and acceleration of the northing respectively. θ, s are outputs of the rate gyro and the odometer respectively.

Assuming the sampling interval is T, the discrete-time nonlinear DR system can be described by a dynamic state-space model as follow:

$$X(k) = \Phi(K / K - 1) + W(K - 1) \qquad (2)$$

$$Y(k) = h[k, X(k)] + V(k) \qquad (3)$$

where, $W(k-1)$ is the process-noise matrix;

$$\Phi(k/k-1) = diag\{\Phi_e, \Phi_n\}$$

And, $$\Phi_e = \Phi_n = \begin{bmatrix} 1 & T & T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$$

the observation vector is

$$h[k, X(k)] = \begin{bmatrix} \arctan\left[\dfrac{v_e(k)}{v_n(k)}\right] \\ T\zeta\sqrt{v_e^2(k)+v_n^2(k)} \end{bmatrix}$$

ζ is scale coefficient of odometer; For more deduction details, see[1,2].

It is obvious that the measurement equation (3) is nonlinear, which is difficult for filtering.

2.2 The state-estimation problem of DR system

The objective of state-estimation is to obtain an estimate state $\hat{X}(k)$ at time K, by utilizing of the previous states, $X(k\text{-}1)\ldots X(k\text{-}n)$, and the sensor values $Y(k)$.

3. The EKF method of solution

The EKF for nonlinear state filtering consists of two steps:

In step 1, the EKF linearizes the nonlinear measurement equation 3 through a truncated Taylor-series expansion at the first updated estimation state, $\hat{X}(k/k-1)$, for the purpose of obtaining the linear measurement equation for state-estimation as formula (4):

$$Y(k) = H(k)X(k) + R(k) \qquad (4)$$

where, $H(k) = \left.\dfrac{\partial h[X(k)]}{\partial X(k)}\right|_{X(k) = \hat{X}(k/k-1)}$ is the Jacobians of $h[\bullet]$

In step 2, the standard KF is employed for state-estimation. For the special algorithms and more details, see [1, 2].

The EKF can be viewed as providing “first-order” approximations to the optimal terms. Furthermore, the EKF does not take into account the “uncertainty” in the underlying random variable and random noise, which often result in inaccurate state estimates, even filtering convergence.

4. The recurrent neural network of

solution

The proposed recurrent neural network of solution is based on the EKF in this paper, which structure is showed in Fig.1. The input of the recurrent neural network is the measurement vector, $Y(k)$, and the output is the state estimates, $\hat{X}(k)$. Obviously, the purpose of the recurrent neural network of solution is obtaining the state estimates by utilizing of the sensor values.

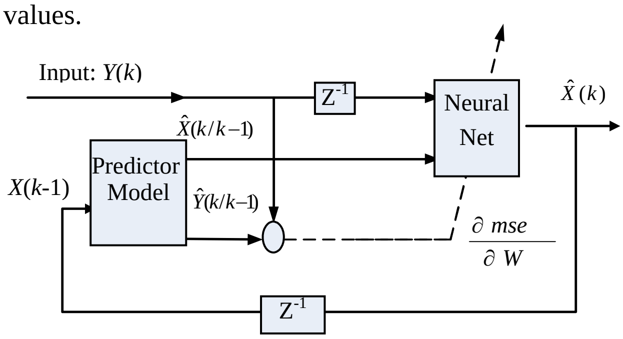

Fig.1 The recurrent neural network

There is only one neural network proposed, however, there are two phases for state-estimation in the neural network method of solution: off-line approximating the nonlinear function and on-line estimating the states.

In the first phase, the system is simulated numerically by providing the system input signals that will typically be encountered during its normal operation. Here the state vectors are assumed known, obtained from the available model. In the second phase, the system is assumed to be in real operation and the states are not assumed available. Input and output data are collected and further training is performed to fine tune the parameters of the filter.

Regardless of the system noises and the measurement noises, the deterministic prediction-update equations can be proposed with the form of (5):

$$\begin{cases} \hat{X}(k/k-1) = \Phi(k/k-1)X(k-1) \\ \hat{Y}(k/k-1) = h[k, X(k/k-1)] \end{cases} \tag{5}$$

and the state-estimation formula is as (6):

$$\hat{X}(k) = \hat{X}(k/k-1) + K(k)\{Y(k) - h[\hat{X}(k/k-1)]\} \quad (6)$$

Furthermore, the state-estimation formula (6) can be written as the form of (7):

$$\hat{X}(k) = K_{NN}[\hat{X}(k/k-1), Y(k)] \tag{7}$$

where, $K_{NN}[\bullet]$ is the nonlinear function equivalent in functionality to the EKF gain.

In contrast to the EKF algorithm, a prediction and an update equation for the error covariance matrix is not included. In the neural network method of solution, the state filter equations (5) and (7) are available.

Phase 1. Off-line approximating the nonlinear function

In this paper an error back-propagation (BP) network[3] utilizing of a Hecht-Nielsen network model with three layers, which can approach a random nonlinear function[3], is constructed in order to realize approximating the nonlinear function, $K_{NN}[\bullet]$. The network structure is as Fig.2.

In Fig.2, The input layer consists of eight neurons: six representing the elements of the prediction-update state vector, $\hat{X}(k/k-1)$, and two representing the values of the observation at time k, $Y(k)$. The Hidden layer consists of twelve neurons and excitation function is Sigmod form. The output layer consist of six neurons, which representing the state estimates at time *k*, $\hat{X}(k)$.

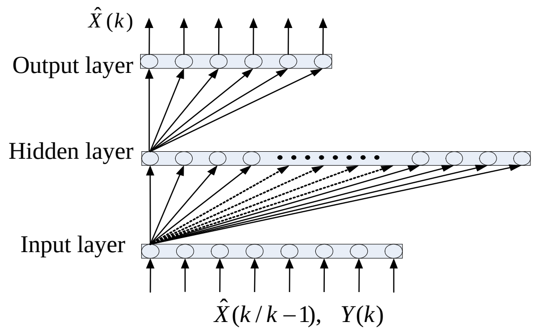

Fig.2 BP network structure

For the training case, a finite set of state values are assumed available, constructed either by model simulations or off-line measurements. The network error function is defined as follows:

$$E_{mse} = \frac{1}{2}\sum_{n=0}^{Np}[\hat{X}(k) - X_{\exp}(k)]^T[\hat{X}(k) - X_{\exp}(k)] \tag{8}$$

Where, $\hat{X}(k)$ is the state-estimation vector; $X_{\exp}(k)$ is the expectation state vector; and *Np* is the number of training examples.

Based on a gradient descent algorithm, the training in this phase will asymptotically converge to the expected value of the target state, given the current and previous outputs and previous state estimates. In this paper, the details of algorithms are not discussed because they follow training principles of the standard BP network.

Phase 2. on-line estimating the states

For the on-line case the states are unknown, the training algorithm becomes more complex. In view of that the states are unknown, the network error function is defined in terms of the system measurement values as follows:

$$mse(k) = \frac{1}{2}\sum_{s=0}^{n}\left[\hat{Y}(k/k-1)-Y(k)\right]^T\left[\hat{Y}(k/k-1)-Y(k)\right] \quad (9)$$

The error gradients of the BP network, $\nabla mse_w(k)$, can be obtained by using the the chain rule as follows:

$$\begin{aligned}\nabla mse_W(k) &= -\alpha\frac{\partial mse(k)}{\partial W}\\ &= -\alpha\left[\hat{Y}(k/k-1)-Y(k)\right]^T\frac{\partial \hat{Y}(k/k-1)}{\partial W}\end{aligned} \quad (10)$$

where, α is the learning rate; *W* contains all of the network weights and biases.

The gradient $\partial\hat{Y}(k/k-1)/\partial W$ can be obtained by differentiating the predictor equation (6) with respect to *W* as follows:

$$\begin{aligned}\frac{\partial \hat{Y}(k/k-1)}{\partial W} &= \frac{\partial h[\bullet]}{\partial \hat{X}(k/k-1)}\times\frac{\partial \hat{X}(k/k-1)}{\partial W}\\ &= \frac{\partial h[\bullet]}{\partial \hat{X}(k/k-1)}\times\Phi(k/k-1)\times\frac{\partial X(k-1)}{\partial W}\end{aligned} \quad (11)$$

The key point is computing the gradient of the state with respect to w, $\partial X(k-1)/\partial W$. Regarding $X(k-1)$ as the state-estimation at time $k-1$, it means that $X(k-1)$ is the output of the BP network at time $k-1$. Obviously, the solution for computing the gradient of $\partial X(k-1)/\partial W$ has been included in the standard training algorithms, for the deduction details, see [3,4].

In sum, the off-line and on-line training phases are complementary and essential for training the network. The off-line training phase can be viewed as the initial training stage used to obtain a good starting point for the on-line training phase; the on-line training phase can results the more accurate state estimates for the off-line approximating and estimating the states in next time in closed-loop form.

In view of that it is impossible to establish the ideal dynamic model of vehicle DR systems, and very difficult to compute Jacobian matrices of the nonlinear system model, the recurrent neural network method is more easy to realize, and can obtain more accuracy results than the EKF especially under indefinite noises, despite the more complicated algorithm frame.

5. Simulation

In order to test the validity of the recurrent neural network in state-estimation of vehicle DR navigation system, the semi-physical simulation is implemented on computer with Matlab7.0 environment.

Supposed that the vehicle moves on a straight-line road, the constant velocity is $10\sqrt{2}$ m/s and the heading is 45. The starting point is (0,0) . In initial time, Thirty points between the line of (-6,-6) to (0,0) can be selected and their state vectors can also be constructed. These vectors are the sampling for off-line training, which will continue to be refreshed in real-time filtering. Select learning rate is 0.1, learning epochs are 300, the Fig. 3 shows the change of the MSE.

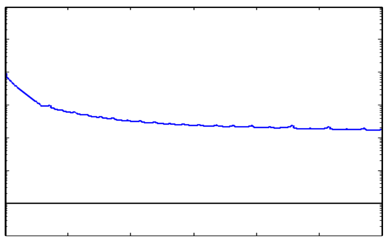

Fig.3 The MSE of off-line training

In fact, the MSE is 0.0061106/1e-005 and the Gradient is 0.0490169/1e-006 at the 50th epoch, and the off-line training can be cancelled.

The simulation time is 200s, and the interferers are increased at time 150s. The simulation results are shown in Fig.4 and Fig.5. In each figure, the real curve is the representation of the result obtained by the recurrent neural network, and the broken curve is that of the EKF.

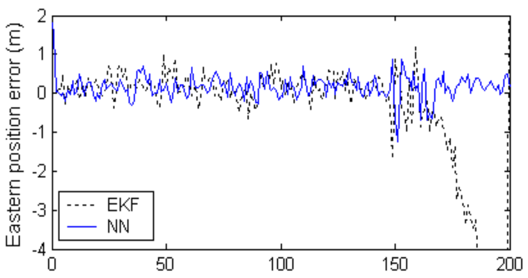

Fig.4 The eastern position estimation error

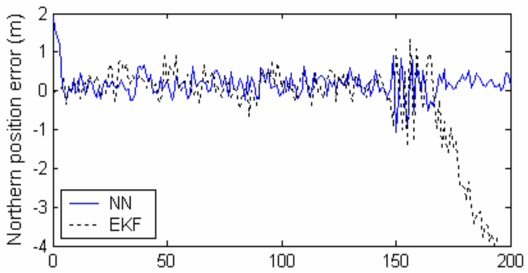

Fig. 5 The northern position estimation error

Where, Fig. 4 shows the eastern position estimation error. Fig. 5 shows the northern position estimation error. It is obvious that the recurrent neural network can result in more accurate estimates of the vehicle DR navigation system than the EKF. Furthermore, when the noises are increased, the interferers seriously affect the accuracy of the EKF and lead to divergence of the filter at last. On the contrary, the recurrent neural network shows a good adaptive ability to resist disturbing.

6. Conclusions

The recurrent neural network, proposed as a solution to state-estimation of the nonlinear vehicle DR navigation system here, addresses the defects of the well known EKF, with the added benefit of ease of implementation in that it need not to calculate the accurate analytic derivation and Jacobians of the nonlinear DR model.

In this paper, the simulation results have show the superior performance of the recurrent neural network method compare to that of the EKF, especially the adaptive ability of resisting interferers. Certainly, it’s expected that the algorithms of the recurrent neural network should be improved and that the method of neural network should perform better than the EKF in some other nonlinear systems and has a widespread use gradually.

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