

Neural Kalman Filter Application to Speech Enhancement

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Abstract– This paper presents a novel approach for speech enhancement by integrating neural network-based system identification with the Extended Kalman Filter (EKF) to address the inherent nonlinearity of voice signals. Traditional linear Kalman filters are ineffective for such nonlinear systems, necessitating advanced methods for accurate estimation and noise reduction. The proposed method consists of two main phases: first, the nonlinear dynamics of a clean speech signal are identified using a Multi-Layer Perceptron (MLP) neural network trained with the Error Back Propagation (EBP) algorithm. This neural network models the speech system in a state-space representation, learning its behavior over 39,000 iterations to achieve a high-fidelity parallel model. In the second phase, the trained neural network model is used within an EKF framework to estimate and enhance noisy speech. The EKF linearizes the nonlinear model at each time step by computing the Jacobian matrix derived from the neural network's input-output relationships. This adaptive linearization allows the filter to perform optimal state estimation even under nonlinear conditions. Key steps include initializing the filter with estimated states and noise variances, performing time updates using the Jacobian matrix, and executing measurement updates to refine the estimates based on observed noisy signals. The experimental validation was conducted using MATLAB simulations, where a clean speech signal was corrupted with additive white noise to create a noisy input. Results demonstrate that the neural network successfully models the clean speech signal, as evidenced by the overlapping of network output and target signals and the convergence of training error to zero. Subsequently, the EKF-based estimator effectively recovers the enhanced speech from the noisy input. Comparative visual analysis of the clean, noisy, and enhanced signals confirms significant noise suppression and improved signal clarity. In conclusion, this study successfully demonstrates that the synergy of neural network identification and Extended Kalman Filtering provides a robust and effective solution for enhancing nonlinear speech signals corrupted by noise. The method overcomes the limitations of linear filters and offers a structured framework for modeling and estimating complex real-world systems, with promising applications in communication, aviation, and multimedia processing where speech quality and intelligibility are critical.

Keywords: Speech Enhancement Extended Kalman Filter, Neural Network.

1. Introduction

Since 1960 the Kalman filter was introduced, always researchers tried to use this filter for linear systems dynamics estimation, however, the main problem was that

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most real systems have nonlinear architecture while the linear Kalman filter is unable to estimate those systems. For instance, voice systems are nonlinear systems that because of voice nonlinearity architecture and linear Kalman filter restriction could not be estimated until an extended Kalman filter was introduced.

This filter creates optimized estimations of nonlinear system states with nonlinear system modelling using a neural network[1-3].

Speech enhancement aims to improve quality and intelligibility. Quality refers to the amount of noise free in

speech and intelligibility refers to the percentage number of words understand in the sentence. Speech enhancement involves noise estimation as crucial part. Many researchers represent different ideas for nonlinear system methods and each one has its own advantages and disadvantages, but a few nonlinear methods are introduced for voice enhancement. In this paper, we introduce a simple algorithm to identify nonlinear voice systems by neural network and then with an extended Kalman filter (EKF) estimation algorithm, improve noisy voice signals. Moreover, at the end of the paper; clean, noisy, and enhanced signals are compared. In conclusion, a comparative analysis demonstrates significant improvement in the proposed method.

2. Speech Identification

In the nonlinear system identification field, voice is also comprised, because nonlinear system dynamics are variable at each time and unpredictable certainly, therefore linear system identification methods are not implemented. The only suitable way for this modelling is by applying neural networks.

Because of learning ability, neural networks and fuzzy neural networks are the only methods in nonlinear systems identification and prediction. These networks can parallel by main system and learn system behaviour intelligently after some iteration. Then, they can operate like the main system and they can be replaced with a modelled system. This extra ability makes possibility to model a lot of nonlinear and difficult real systems dynamics with neural networks[4],[5].

2.1 Voice State Space Representation

Figure 1 shows x_k Signals are the noisy voice production nonlinear system states and v_k Process noise is the system input; the output is y_k Which is a noisy signal destroyed by n_k Measurement noise.

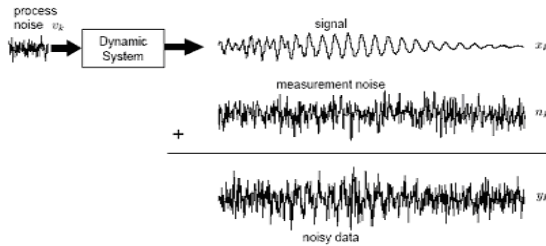


Fig. 1: Data is processed with an AR model and destroyed by added measurement noise.

The system state space representation is as below[6]:

$$X_k = F(X_{k-1}, W) + B.V_k \quad (1)$$

$$\begin{bmatrix} x_k \\ x_{k-1} \\ \vdots \\ x_{k-M+1} \end{bmatrix} = \begin{bmatrix} f(x_{k-1}, \dots, x_{k-M}, W) \\ 1 & 0 & 0 & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_{k-1} \\ \vdots \\ x_{k-M} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \cdot v_k \quad (2)$$

And system output is calculated as below:

$$Y_k = C \cdot X_k + n_k \quad (3)$$

$$y_k = [1 \quad 0 \quad \dots \quad 0] \cdot \begin{bmatrix} x_k \\ x_{k-1} \\ \vdots \\ x_{k-M+1} \end{bmatrix} + n_k \quad (4)$$

2.2 Neural Autoregressive Identification

In this system identification method, is supposed that only system output is known and system input is unknown hence, only output is accessible for identification.

In this communication system, output, that is clean voice, is considered as the network target in the mentioned method, and output feedback is considered as system input:

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y)) \quad (5)$$

Then, the network begins to train as its block representation is shown in Figure 2:

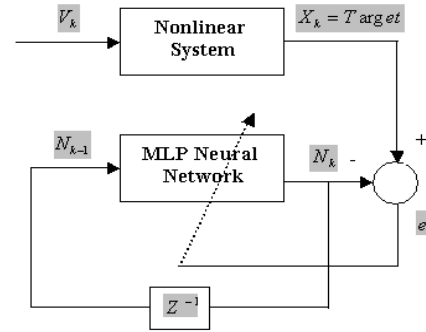


Fig.2: System Identification Loop

For system identification, an MLP neural network is paralleled with the system, and applied system input is used as network input. Also, the system output is defined as a network target signal.

Then with the recurrent error back propagation (EBP) method, the neural network is trained whereas in each iteration, network output is compared with the target, and error is an important item of feedback to the neural network. Since x_k Vector length, that is a voice signal, is 39000, thus at least 39000 iterations are needed for the neural network [7-9].

2.3 Applied Neural Network

To build matrix A that is applied in the extended Kalman filter (EKF) program is needed to linearize nonlinear function F which $F(x_k, w)$ is the network output. This linearization is performed with Jacobin matrix calculation. The Jacobin matrix array consists of input difference divided by output difference. Therefore, matrix A dimension is related to the number of inputs.

In this paper, 5 inputs are assigned to the network; thus, the matrix A dimension is 5.

The network scheme as a feed-forward network, with 5 inputs, 5 hidden layers with tanh fire function, and 1 output with linear fire function that is defined as an order 5 nonlinear model (Figure 3)[10]:

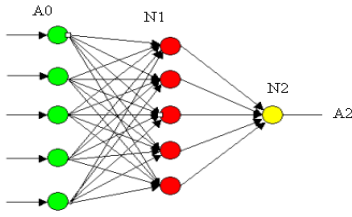


Fig. 3: MLP Neural Network Structure

In the neural network training condition, the important point is that the MLP network is trained with the EBP method.

In this training method, after the first and second network layer calculations, network output is obtained and compared with the target signal; then, the calculated error is feedbacked to the network and is affected by updating weight and bias neural network vector. The network begins a new recurrent iteration whereas posterior time output (y_{k-1}) is applied as a prior input (x_k).

Also forgetting factor is defined as an option item that if selected by the operator, weight, and bias updating vector are changed, however, this subject does not change the learning process and only the update equation is varied slightly.

Neural network block-diagram representation by applying this method is as Figure 4:[11]

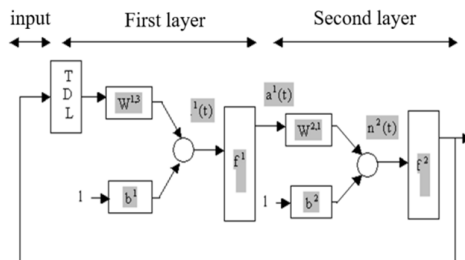
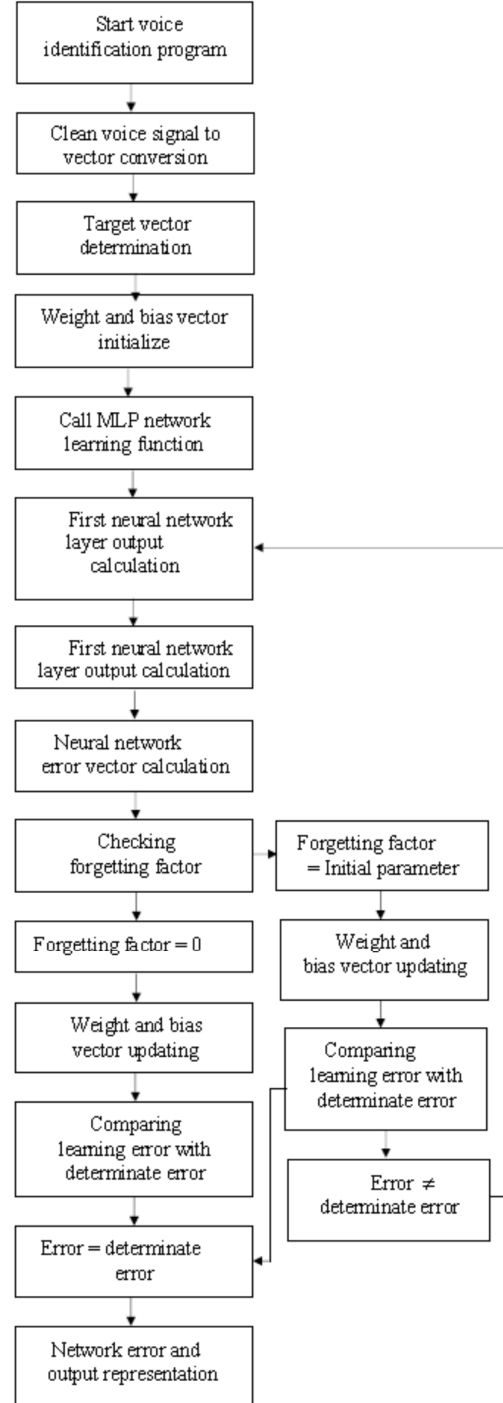


Fig.4: Neural network block diagram representation that trained with EBP method

2.4 Voice Identification Flowchart

In this flowchart, voice identification steps that consist

of initializing, calculating, updating, and comparing network training parameters are shown separately.



3. Voice EKF Estimation

According to the mentioned voice identification steps, which lead to modelling and system dynamics identification,

nonlinear model dynamics should be estimated. But here because of the nonlinear model, EKF should be used instead of the Kalman filter. EKF is an approximate method for nonlinear models that estimates these models as a time-variant linear model.

This point is important to mention, according to the invariant Kalman filter property, it is highly needed that system dynamics be known. On the other hand, for signal estimating with all kinds of Kalman filters, model estimation (modelling) is an important item.

In the following section, EKF equations are represented[12]:

3.1 Initialize

$$\begin{aligned}\hat{x}(0) &= E(x_0) \\ P_0 &= E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]\end{aligned}\quad (6)$$

These equations show that the first input vector and then noise variance are initialized.

3.2 Time Update Equations

Then, time update equations are introduced. A_k Vector is the most important segment and it is obtained by derivation of F Function, which is an MLP neural network. To manipulate this vector, a Jacobin matrix is needed with arrays in which the irnumerators are the difference between two prior and posterior outputs and their enumerator are the difference between two present and previous inputs. These array numbers also depend on neuron numbers in the network input layer. In this paper, the number of neurons in the first layer is 5, so the matrix. A_k Dimension is 5*5.

This point is important. A_k The matrix is changed by index k, which varies from 1 to 39000, and it is not constant like the matrix. A In the Kalman filter time update equation.[13]

$$A_k = \frac{\partial F(X, W)}{\partial X} |_{x = \hat{x}_k} \quad (7)$$

$$A_k = \begin{bmatrix} \frac{\partial f(\hat{x}_k, w)^T}{\partial x} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \ddots & 0 & \ddots \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{bmatrix} \quad (8)$$

$$\begin{aligned}\hat{x}_k^- &= F(\hat{x}_{k-1}, w) \\ P_k^- &= AP_{k-1}A^T + B\sigma_v^2B^T\end{aligned}\quad (9)$$

3.3 Measurement Update Equations

In the measurement update equation too, gain K and signal estimation and noise of variance are updated.

$$\begin{aligned}K &= P_k^- C^T (CP_k^- C^T + \sigma_n^2)^{-1} \\ \hat{x}_k &= \hat{x}_k^- + K(y_k - C\hat{x}_k^-)\end{aligned}\quad (10)$$

$$P_k = (I - KC).P_k^-$$

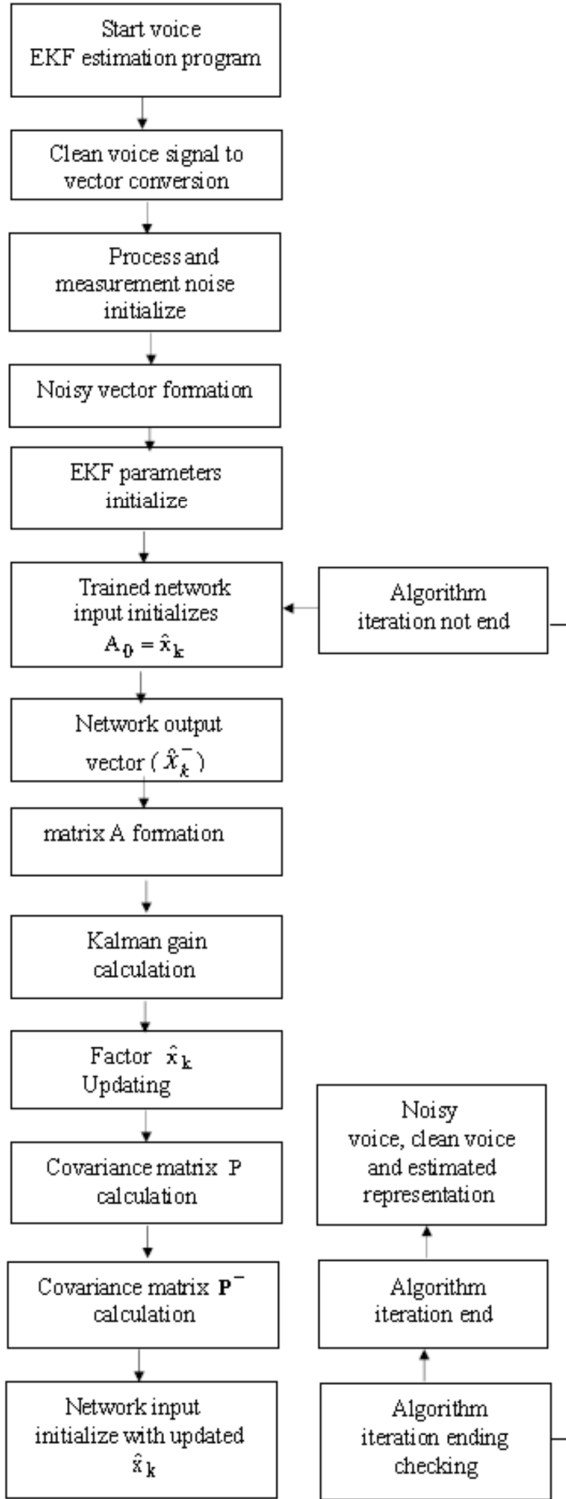
As an example, the condition of obtaining a matrix A_6 That is the first matrix. A In program circle is as below:

$$A_6 = \begin{bmatrix} \frac{\hat{x}_7^- - \hat{x}_6^-}{\hat{x}_2^- - \hat{x}_1^-} & \frac{\hat{x}_7^- - \hat{x}_6^-}{\hat{x}_3^- - \hat{x}_2^-} & \frac{\hat{x}_7^- - \hat{x}_6^-}{\hat{x}_4^- - \hat{x}_3^-} & \frac{\hat{x}_7^- - \hat{x}_6^-}{\hat{x}_5^- - \hat{x}_4^-} & \frac{\hat{x}_7^- - \hat{x}_6^-}{\hat{x}_6^- - \hat{x}_5^-} \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

Then by using a matrix A_6 in the measurement update equation, \hat{x}_6 Is calculated; these calculations are iterated 39000 times, so iterations continue until \hat{x}_{39006} Is calculated and the results are saved in program memory; they call back at the end of the program and compare with the clean voice.

3.4 Voice EKF Estimation Flowchart

In this flowchart, clean voice estimation steps that consist of initializing, calculating, updating, and comparing parameters are shown separately.



4 Results

First, neural network output and clean signal, which train network, are represented. Figures No. 5 to No. 8 are simulated with MATLAB 7.1 software.

In Figures 5 and 6 voice identification is demonstrated with a neural network.

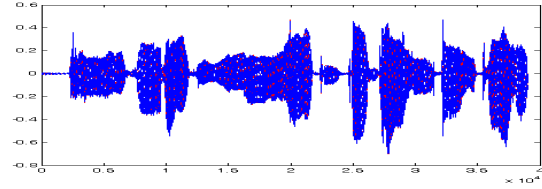


Fig. 5: Comparing network output (blue graph) with target signal (red graph)

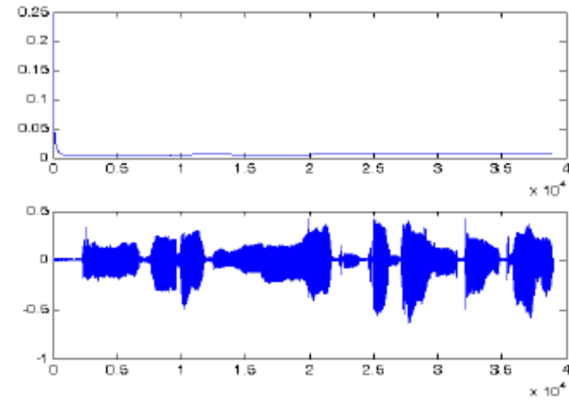


Fig. 6: network training error (first graph) and network output (second graph) representation

As specified in Figure 6, nonlinear voice is modelled well and the network output signal and target signal, which is clean voice, have obviously overlapped. Also, network training error, which is the sum of squared error and is obtained from the difference between the target signal and network output, converges to zero. That is the reason for network convergence.

In addition, we represent the estimated voice signal that is obtained by voice modelling and then voice estimation with EKF (Figure 7).

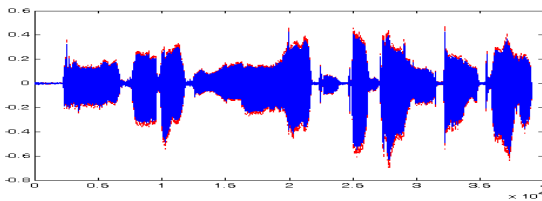


Fig. 7: Compare clean voice signal (red graph) with estimated voice signal (blue graph)

Finally, figure 8 represents 3 graphs. First, a clean voice signal is considered a neural network target for training. The second is, a noisy signal which is the conclusion of

adding white noise with known variance to the clean voice signal, and the third is, the estimated voice signal that is obtained by EKF.

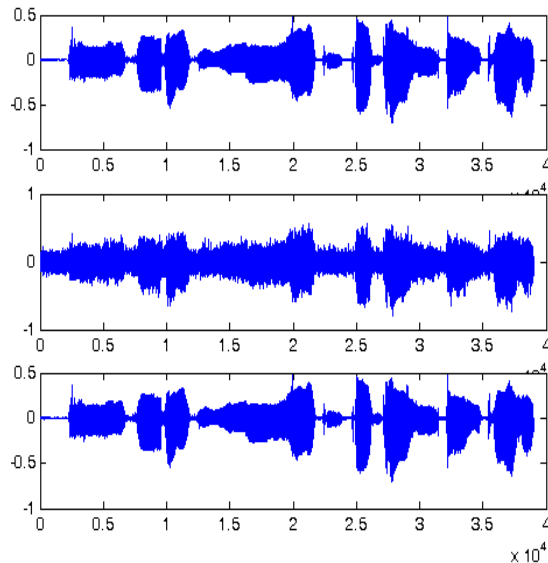


Fig. 8: Representation and comparison of clean voice signal (first graph), noisy signal (second graph), and estimated voice signal (third graph)

5 Conclusions

In conclusion, it is clear that neural networks in many cases in which classic control cannot be used, act well for system identification or modelling and can be applied with EKF to estimate nonlinear system dynamics as voice signals.

Also, it is shown that EKF is able to give certain estimations of nonlinear system dynamics, which are identified by neural networks and it is useful for researchers in control and communication fields.

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