Extended Kalman Filter Method based on Backpropagation Neural Network in Current Sensor Online Calibration

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Abstract. The signal collected by current sensor will contain various noises, which will have a negative impact on its accuracy and calibration. In order to remove unwanted noises, an extended Kalman filter (EKF) method based on backpropagation (BP) neural network is proposed in this paper. BP neural network has good adaptive ability and non-linear mapping ability. EKF can effectively filter noise and improve the calibration accuracy for non-linear systems. The signal collected by current sensor is processed by EKF and is used as the input signal of BP neural network. The trained neural network can modify the output signal of EKF, so as to improve the calibration accuracy. The angle difference and ratio difference of current sensor calibration are below 0.1, which meets the national standard and shows the effectiveness of this method.

1. Introduction

In general, any equipment or device that is used to perform measurements should be regularly calibrated. In the same vein, as an important equipment in power systems, a current sensor should be periodically verified to ensure the accuracy of its output.

The data collected by current sensor is influenced by many factors, which will produce various kinds of clutter, mainly including white noise and colored noise. Kalman filter is the most commonly used filtering method [1]. Ordinary linear Kalman filter requires linear systems in applications, but there is always a certain degree of nonlinearity in the practical application system. Thus extended Kalman filter (EKF) [2], unscented Kalman filter (UKF) [3] and adaptive Kalman filter (AKF) [4] have been developed. EKF uses local linearization method to transform the problem into a linear system so that the local optimal solution of the problem can be obtained. The premise of Kalman filter application is that the statistical characteristics of state noise and observation noise are known and remain unchanged [5], but this cannot be guaranteed in many engineering applications. Noise may be non-priori and not unchanged. Besides Kalman filter requires strict initial values, otherwise it is easy to cause non-convergence. We can use backpropagation (BP) neural network to modify EKF adaptively.

Artificial neural network is a computational system developed on the basis of simulating human brain nerve tissue. It is a network system composed of a large number of processing units through extensive interconnection. It is a kind of simulation of biological system. With the advantages of large-scale parallel, distributed processing, self-organization and self-learning, artificial neural
network has been widely used in speech analysis, image recognition, digital watermarking, computer vision and many other fields [6]. Wei et al. designed adaptive neural network control for the robotic system with full-state constraints [7]. In [8], neural network is used to guarantee the accuracy and efficiency of diagnoses due to multiple, complex and uncertain conditions of computer networks.

Artificial neural network mainly includes convolutional neural network (CNN), recurrent neural networks (RNN), Boltzmann machine model [9-11]. In [12], a new method for improving the performance of recurrent neural network is proposed for images classification. BP neural network [13-14] is a multilayer feedforward neural network trained by error back propagation algorithm, and it is the most widely used neural network.

This paper combines extended Kalman filter with BP neural network for data processing. Then, the proposed method is used to perform online calibration of a current sensor to demonstrate its efficacy.

2. Current sensor calibration principle

The current sensor online calibration system is comprised of a standard channel and calibration channel, synchronous control module, data acquisition module, and data processing module. As shown in Fig. 1, current sensor and standard sensor begin to collect data at the same time and save the data to computer. Then, the data are processed and the calibration indexes are obtained. The data collected by current sensor have a variety of clutter, such as white noise and colored noise. In order to ensure the accuracy of calibration, it is necessary to filter out useless signals. This is the role of the data processing system.

![Diagram of the online verification principle for current sensors.](image)

The two primary indexes for current sensor calibration are ratio difference and angle difference. Ratio difference is an error value that represents the difference between the actual current sensor ratio and nominal ratio, which are not equal in real-world scenarios. For digital outputs, the ratio difference is expressed as:

$$\varepsilon = \frac{K I_S - I_P}{I_P} \times 100\%$$

(1)

Where \(K\) is nominal transformation ratio, \(I_P\) is the root mean square value of the primary current when primary side residual current equals zero, and \(I_S\) is the root mean square value of the digital output when the sum of secondary side residual output current and secondary side DC output equals zero.
Furthermore, the definition of angle error definition is divided into two, one for analog outputs, and one for digital outputs [15]. For an analog output, the angle difference between the primary and secondary signals at the time of measurement is defined as angle error, whereas for a digital output, the difference between the time at which a current is recorded and the time at which the data is transmitted at the secondary end is defined as so. The electronic current sensor phase difference φ is the difference between the phase of the primary current phasor and secondary output phasor; the phasor direction is selected such that the phase difference angle of the ideal sensor is equal to its rated value at the rated frequency. The phase difference is positive when the secondary output phasor leads the primary current phasor.

3. Data processing algorithms

In this subsection, we will describe the data processing algorithm of current sensor calibration.

3.1 Extended Kalman Filter

There is always a certain degree of nonlinearity in the practical application system and common linear Kalman is only suitable for linear situations. For nonlinear systems, local linearization method is used to transform them into approximate linear systems. This is the basic principle of extended Kalman filter (EKF). EKF truncates the Taylor expansion of the nonlinear function by first order linearization and ignores the other higher-order terms, thus transforming the nonlinear problem into a linear one [16].

The function model of extended Kalman filter is

\[ X_{k+1} = f(X_k) + W_k \]  
\[ Y_k = h(X_k) + V_k \]

Where \( X_k \) is the system state vector of time \( k \); \( Y_k \) is the system observation vector of time \( k \); \( W_k \) and \( V_k \) are the state noise and observation noise respectively.

The recursive formulas of the extended Kalman filter are as follows.

The one-step prediction equation is

\[ X_k^- = f(X_{k-1}) \]  
\[ P_k^- = FP_kF^T + Q \]

Filter gain is

\[ K_k = P_k^-H^T(HP_k^-H^T + R)^{-1} \]

Covariance updating equation is

\[ P_k = (I - K_kH)P_k^- \]

State updating equation is

\[ X_k = X_k^- + K_k(Y_k - h(X_k^-)) \]

Where \( Q \) and \( R \) are both covariance matrices. \( I \) is unit matrix. \( F \) and \( H \) are the first derivative of \( f[\cdot] \) and \( h[\cdot] \) respectively.

3.2 BP Neural Network

Neural network is a model of imitating biological nervous system, which is a black box model. The most commonly used model is M-P model, as shown in Fig. 2. This neuron receives signals from other \( n \) neurons and transmits them through weighted connections.
Each input signal $X_i$ and its corresponding weights $w_{ki}$ are added by weights, and then the output signal $Y$ is obtained by transfer function operation, i.e., $\sigma$. In particular, the external bias can be regarded as a synapse with input as 1 and synaptic weight as $b_k$. The learning process of neural network is to use a large number of examples to repeat training of the network until the synaptic weights are not significantly modified. At this time, the neural network reaches a stable state and the training stops.

BP neural network is a multilayer feedforward neural network based on error back propagation learning algorithm. One BP neural network usually consists of one input layer, one or more hidden layers and one output layer [17]. The structure diagram is as follows.

3.3 Extended Kalman Filter Based on BP Neural Network

We can make use of the good adaptive ability and nonlinear mapping ability of BP neural network to self-adaptive correction. We take the output of Kalman filter as the input of the neural network. The output signal of EKF can be modified according to the actual operation, so as to improve the filtering effect.

The variables affecting the filtering accuracy of EKF are selected as inputs of the BP neural network. They are

1) The difference between one-step prediction and state estimation, $X_{k+1|k} - X_{k+1|k+1}$
2) The difference between the observed and estimated values and filter gain, $Y_{k+1} - h(X_{k+1|k})$
3) Filter gain, $K_{k+1}$

The difference between the expected state variable value and the actual state estimation, i.e.,
$X_{k+1} - X_{k+1|k+1}$ is selected as the output of the BP neural network. The output value of BP neural network is the correction of the EKF output signal. By adding the output signal of the BP neural network and the EKF state estimation value, the revised state estimation value can be obtained. As shown in Fig. 4.

![Figure 4. Structural Diagram of EKF Algorithms Based on BP Neural Network.](image)

### 4. Experiments

We conducted online calibration experiment of current sensor to see if it meets 0.1 level standard. As shown in Fig. 5. The current sensor to be verified is marked as 1. The sensor marked as 2 is a standard current sensor and is used as a reference for verification.

![Figure 5. Current sensor calibration experiment.](image)

We adjust the primary input current of current sensor for calibration at 20%, 40%, 60%, 80%, 100% and 120% of the rated current respectively. The experiment results are shown in Fig. 6. The results show that both angle difference and ratio difference of current sensor are lower than 0.1, which meets the national standard. In particular, we find that the angle difference and ratio difference are greater than 0.1 when the input current is small. After analysis, we found the reason. When the input current is small, it will be greatly disturbed by the noise signal. With increasing the input current gradually, we can see that both angle difference and ratio difference are lower than 0.1, which proves the validity of this method.
5. Conclusion
In this paper, a data processing method using BP neural network to modify extended Kalman filter is proposed. And we apply it to the data processing of current sensor online calibration. From our experimental results, it is demonstrated that the proposed method achieved good results. Furthermore, its underlying principle can be extended to more applications, especially where filter processing and neural network are needed.

Acknowledgments
Shuang Zhao thanks professor Li for his constructive guidance.

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