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Predictive Algorithm of Network Delay Based on Robust Kalman Filter

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Abstract. Due to irregular information flow for NCS (Networked Control System), network delay has performance of random and variability. It reduces system stability, network performance and control performance. This paper focuses on research of predictive algorithm of network delay. Network delay data is obtained in PROFIBUS-DP. Based on network delay data, the ARMA (Auto-Regressive and Moving Average) model of delay is set up. The parameter estimation algorithm of Robust Kalman is used to estimate parameters of proposed ARMA model of network delay. A simulation example is given and verifies efficiency of predictive algorithm proposed.

Introduction

Sensor, controller and actuator transfer data through network, which is inevitable to bring delay. In communication network, network delay is an important parameter for network performance [1]. Due to irregular information flow for NCS, network delay has random. It reduces system stability, network performance and control performance. So research of delay is significant.

In order to improve performance and stability of NCS, predictive algorithm of network delay is researched. At present, predictive algorithm of network delay have three kinds of discrete delay model, continuous delay model. In discrete delay model, (LS-SVM) is used to estimate online for random and variable delay in NCS [2]. For continuous delay model, estimated model combines with EM algorithm [3].

This paper includes six parts: The measurement method of network delay is proposed for PROFIBUS-DP NCS in section 2. And the experimental data is obtained. In section 3, the model of delay is set up, which is ARMA model. In section 4, the parameter estimation algorithm of Robust Kalman is presented. Algorithm of Robust Kalman is used to estimate parameters of proposed ARMA model of network delay. In section 5, a simulation example is given to verify efficiency of predictive algorithm of network delay. In section 6, some conclusion is made.

Measurement of Network Delay

Fig. 1 shows distribution of delay. In Fig. 1, network delay for NCS includes two parts. One is the execution delay of τ^s, τ^c and τ^a, the other is the transmission delay of τ_{sc} and τ_{ca}.

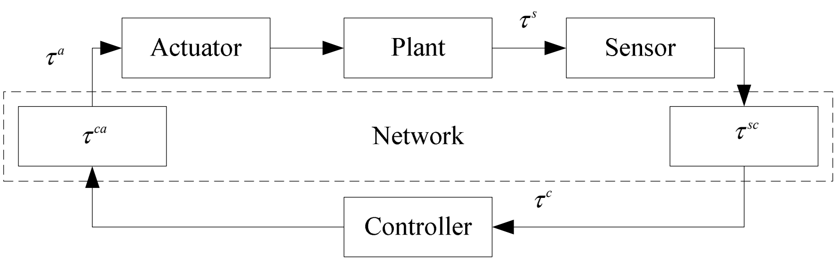

Fig. 1. Distribution of delay

This paper focus on research of the transmission delay τ_{sc} and τ_{ca}. τ_{sc} refers that the delay from sensor to controller. τ_{ca} means that controller sends signal to actuator through network. So network delay τ is defined as $\tau = \tau_{sc} + \tau_{ca}$.

According to whether to send probe packets, measurement techniques of network delay can be included in active measurement, passive measurement and measurement techniques based on the monitored control information. Because active measurement method is considered the measurement process has the advantage of high controllability, measure ease of point to point network. In this paper, flag of data packets is applied to get the network delay from master controller to the slave controller through PROFIBUS-DP network. A Siemens CPU315-2DP PLC is used as master station, three CPU315-2DP PLC are used as slave stations. Fig. 2 shows Communication of master and slave. The master sends data packets through the system function block of SFC15. The last one is set as flag. While the system function block of SFC14 receives the flag, the slave station sends data packet with flag through the system function blocks SFC15. When the master station receives flag of data packets through the system function blocks SFC14, the master station simultaneously records the current system clock. So a round-trip packet delay is obtained. The organization block of OB35 is used to send a data packet every 100ms at master station. Therefore, a sample of network delay is obtained and stored.

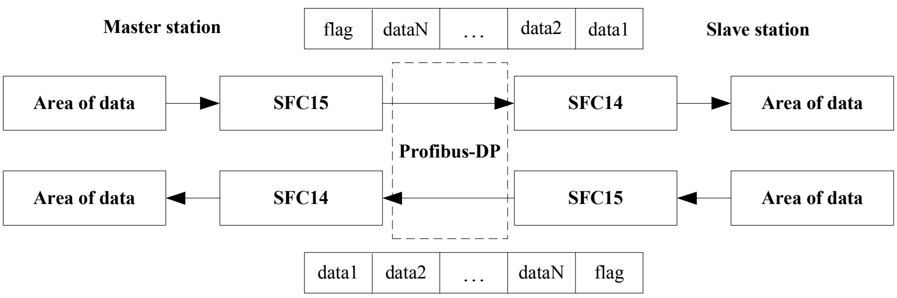

Fig. 2. Communication of master and slave

Network Delay Based on ARMA Model

Because the network delay have performance of random variability, the general linear model and the stochastic model are difficult to describe the network delay. The round-trip delay $\tau(i)$ will be used to describe network delay as master station controller to the slave station controller of PROFIBUS-DP network. The basic idea is based on ARMA model: This network delay sequence is seen as a random sequence. The sequence of the network delay is not only dependent on the historical network delay, but also the historical disturbance. From the analysis of network delay, Auto-Regressive and Moving Average (ARMA) model is presented for historical network delay, which is with fixed constant and unknown white noise. Therefore, ARMA model is established as formula (1).

$$A(q^{-1})\tau(i) = B(q^{-1})\varepsilon(i) \tag{1}$$

$$A(q^{-1}) = 1 + d_1 q^{-1} + \cdots + d_m q^{-m} \tag{2}$$

$$B(q^{-1}) = 1 + e_1 q^{-1} + \cdots + e_n q^{-n} \tag{3}$$

Then the ARMA model of formula (1) can be converted into formula (4)

$$\tau(i) + d_1\tau(i-1) + \cdots + d_m\tau(i-m) = \varepsilon(i) + e_1\varepsilon(i-1) + \cdots + e_n\varepsilon(i-n) \tag{4}$$

where $d_1,\cdots,d_m$ is AR parameters; $e_1,\cdots,e_n$ is MA parameters; $\{\tau(i)\}$ is described as network delay sequence; $\{\varepsilon(i)\}$ is defined as unknown white noise with zero mean，and its known covariance is R. It is known as ARMA (m,n).

Prediction of Network Delay Based on ARMA Model

Currently, there are three methods for ARMA model parameter estimation, which are recursive extended least squares method, maximum likelihood estimation method and Robust Kalman filtering method. The output of RELS convergences slowly for MA (moving average) parameters. In order to improve the convergence of MA parameters, this section presents parameter estimation method of Robust Kalman filter. Robust Kalman filter is changed by unknown mean and covariance matrix of virtual noise, the unknown model errors fall into the virtual noise. So the model parameters have been transformed into unknown noise. This algorithm calculates unknown parameters d_i and e_i, which is based on observation values $(\tau(i), \tau(i-1), \cdots, \tau(1))$.

Unknown vector is defined as formula (5).

$$\phi = [d_1, \cdots, d_m, e_1, \cdots e_n]^T \tag{5}$$

State-space model is described as formula (6) and (7).

$$\phi(i+1) = \phi(i) \tag{6}$$

$$\tau(i) = H(i)\phi(i) + \varepsilon(i) \tag{7}$$

Then time-varying matrix $H(i)$ is defined as formula (8).

$$H(i) = [-\tau(i-1), \cdots, -\tau(i-m), \varepsilon(i-1) \cdots \varepsilon(i-n)] \tag{8}$$

But $H(i)$ contains unknown white noise $\varepsilon(i-1) \cdots \varepsilon(i-n)$, $\omega(i-k)$ is replaced by estimation $\hat{\omega}(i-k)$, so observation equation is rewritten as formula (9)

$$\tau(i) = \hat{H}(i)\phi(i) + \omega(i) \tag{9}$$

$\hat{H}(i)$ is defined as formula (10).

$$\hat{H}(i) = [-\tau(i-1), \cdots, -\tau(i-m), \hat{\varepsilon}(i-1) \cdots \hat{\varepsilon}(i-n)] \tag{10}$$

where $\omega(i)$ is seen as virtual white noise, it compensate error of observation noise.

Robust Kalman filter about ϕ is shown as follows.

$$\hat{\phi}(i+1) = \hat{\phi}(i) + S(i+1)\hat{\varepsilon}(i+1) \tag{11}$$

$$\hat{\varepsilon}(i+1) = \tau(i+1) - \hat{H}(i+1)\hat{\phi}(i) - \hat{r}(i) \tag{12}$$

$$S(i+1) = P(i+1|i)\hat{H}^T(i+1)[\hat{H}(i+1)P(i+1|k)\hat{H}^T(i+1) + \hat{R}(i)]^{-1} \tag{13}$$

$$P(i+1|i) = [I - S(i)\hat{H}(i+1)]P(i|i-1) \tag{14}$$

$$\hat{r}(i+1) = (1-d_i)\hat{r}(i) + d_i[\tau(i+1) - \hat{H}(i+1)\hat{\phi}(i+1)] \tag{15}$$

$$\hat{R}(i+1) = (1-d_i)\hat{R}(i) + d_i[(1-H(i+1)K(i+1))^2]\hat{\varepsilon}^2(i+1) + H(i+1)P(i+2|i+1)H^T(i+1)] \tag{16}$$

Initial value of $\hat{\phi}(0)$ is set ϕ_0, initial value of $\hat{r}(0)$ is r_0, initial value of $\hat{R}(0)$ is R_0, initial value of $P(1|0)$ is $P(0)$, $d_i = (1-b)(1-b^{i+1})$ is with $0 < b < 1$, and b is forgetting factor[4].

According to minimum variance prediction method, the network delay of next sampling time $\hat{\tau}(i)$ can be obtained from formula (15):

$$\hat{\tau}(i) = \hat{H}(i)\hat{\phi}(i) \tag{17}$$

Simulation

In order to verify availability of Robust Kalman filter, an example of prediction of network delay is given. Fig. 3 shows predictive output of network delay. It can be seen that next period network delay is predicted by Robust Kalman filter.

$$\tau\ (i+1)+d_1\tau(i)+d_2\tau(i-1)+\cdots+d_m\tau(i-m+1)=\varepsilon\ (i+1)+e_1\varepsilon(i)+e_2\varepsilon(i-1)+\cdots+e_n\varepsilon(i-n+1) \quad (18)$$

Fig. 3 shows predictive output of network delay. From Fig. 3, it can be seen that the output of network delay convergences rapidly. Due to fewer data of network delay, at initial period predictive values convergences slowly. But when delay data increase, predictive values approach to real values. From simulation results, minimum variance is applied to predict next period network delay.

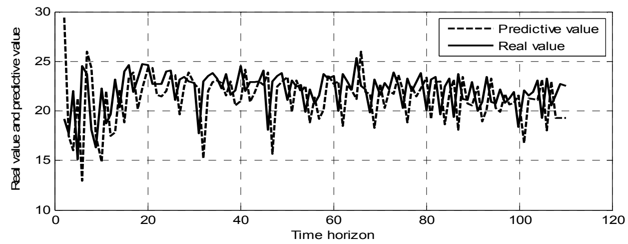

Fig. 3. Predictive output for network delay

Fig. 4 shows error trajectories of network delay. In Fig. 4, it can be seen that predictive error of network delay is larger than real values at initial period. But when delay data increase, error of predictive values and real values cut down. From simulation results, predictive values track well to desired values.

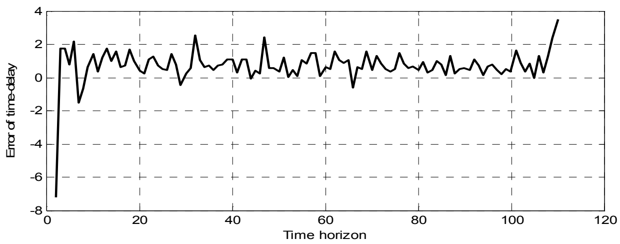

Fig. 4. Error trajectories of network delay

Conclusion

The Robust Kalman filter is applied to obtain parameters estimation of ARMA model of network delay. The results of simulation show that predictive value of network delay is close to the actual measurement value of network delay.

Acknowledgements

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References

[1] Xiaoshuo Huang, Yan He and Jingping Jiang: Journal of Scientific Instrument, Vol. 33 (2012), p. 1968 (In Chinese)

[2] Chunmao Li: Journal of Southwest Jiao tong University, Vol. 42 (2007), p. 175 (In Chinese)

[3] M F. Shih and A O. Hero: IEEE Transaction on Signal Processing, (2003), p. 2219

[4] Zili Deng and Jianguo Wang: Information and Control, (1988), p.1 (In Chinese)