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Fault Location Estimation using Estimator Residual

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Abstract

Reflectometry is a kind of cable fault diagnosis. There are various kinds of reflectometries such as time domain reflectometry(TDR), frequency domain reflectometry(FDR), and joint time-frequency domain reflectometry(TFDR). In this paper, we propose a new fault location estimation method using residual of AR coefficient estimation. Proposed fault distance estimation method models the reference signal as a simple second order AR coefficient, and estimates reference signal and reflected signal via robust weighted least square(RWLS) estimator. Using residual of estimation, proposed fault distance estimator estimates the fault location of the cable. The performance of the proposed method is verified by simulations and experiments.

1 Introduction

Defected cable may cause fatal disaster. In order to prevent disaster, fault detection method is needed. There are many kinds of cable fault diagnosis. The reflectomery that stems from sonar and radar system is one of the cable fault diagnosis. There are various reflectometries, such as TDR, FDR, and TFDR. Each reflectometry has different analysis method and characteristics[1]. However, main idea of reflectometry is the same. At the fault location of cable, transmitted reference signal is reflected due to the impedance miss matching. Fault location is estimated based on the time delay between the reference signal and the reflected signal.

The Gaussian enveloped linear chirp signal is adopted as a reference signal on the TFDR method. In the TFDR, the joint time-frequency energy distribution of the reference signal and reflected signals is computed. And the time-frequency cross correlation is computed using the joint time-frequency distribution. The time delay information is obtained from the time-frequency cross correlation[1]. Accurate fault distance estimation in the TFDR is possible due to the time-frequency cross correlation function. However, the computational burden is a fatal obstruct to do the real-time implementation. From the view point of the estimator for the time delay between the reference signal and the reflected signal, cable fault diagnosis is interpreted as a signal modeling and estimation problem. In time of arrival estimation problem, the reflected signal is modeled as an attenuated and time delayed version of the reference signal, and use the least square(LS) estimator to estimate the time delay[4]. In this paper, we introduce another approach to time delay estimation. Reference signal is modeled with second order AR coefficients for minimizing the computational burden. The RWLS[2] estimator is designed to estimate the AR coefficients. When the reference signal or the reflected signal is detected, residual has peak amplitude that is due to the conversions rate of the RWLS estimator. Using this phenomenon, we are able to estimate the time delay.

2 AR Modeling for Chirp Signal

The reflected signal in reflectometry is assumed as an attenuated and time delayed version of the reference signal. If reference signal is modeled via AR coefficient, the reflected signal also satisfies the AR modeling coefficients because the reflected signal is a replica of the reference signal. In this paper, the reference signal is a linear chirp signal that has linearly increasing frequency. The linear chirp signal is represented as follows,

$$\begin{aligned} s_k =& Me^{j(\frac{1}{2}\beta(T_s k)^2+\omega_0(T_s k)-\frac{\pi}{2})} \\ =& M[cos(\frac{1}{2}\beta(T_s k)^2+\omega_0(T_s k)-\frac{\pi}{2}) \\ &+jsin(\frac{1}{2}\beta(T_s k)^2+\omega_0(T_s k)-\frac{\pi}{2})], \end{aligned} \tag{1}$$

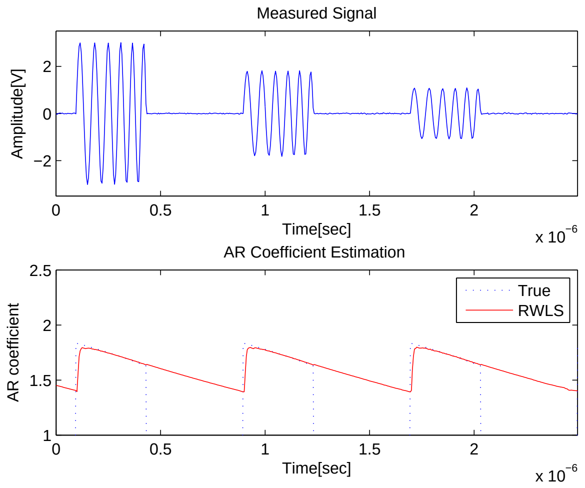

Figure 1: AR coefficient estimation : 100.08m

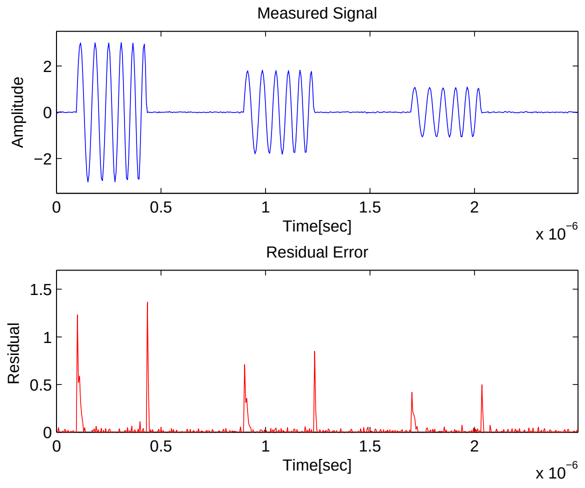

Figure 2: Residual of AR coefficients estimation: 100.08m

where M is the amplitude of linear chirp signal, β is frequency sweep rate, T_s is sampling interval and ω_0 is start frequency. For notational convenience, θ_k is defined as follows:

$$\theta_k = (\frac{1}{2}\beta(T_s(k))^2 + \omega_0(T_s(k)) - \frac{\pi}{2}). \tag{2}$$

Using the θ_k, s_{k-1} and s_{k-2} are given by,

$$s_{k-1} = M[cos(\theta_{k-1}) + jsin(\theta_{k-1})]. \tag{3}$$
$$s_{k-2} = M[cos(\theta_{k-2}) + jsin(\theta_{k-2})]. \tag{4}$$

For deriving the AR coefficients equation, s_k is rewritten by,

$$\begin{aligned} & s_k + s_{k-2} \\ =& 2Mcos(-\beta T_s^2(k-1) - \omega_0 T_s) \\ & \times [cos(\frac{1}{2}\beta T_s^2)\{cos(\theta_{k-1}) + jsin(\theta_{k-1})\} \\ & + jsin(\frac{1}{2}\beta T_s^2)\{cos(\theta_{k-1}) + jsin(\theta_{k-1})\}] \\ =& 2cos(-\beta T_s^2(k-1) - \omega_0 T_s) \\ & \times \Big(cos(\frac{1}{2}\beta T_s^2) + jsin(\frac{1}{2}\beta T_s^2)\Big) s_{k-1} \end{aligned} \tag{5}$$

For notational convenience, A_k is defined as follows:

$$A_k = -\beta T_s^2(k-1) - \omega_0 T_s. \tag{6}$$

Equation(5) is can be rearranged by,

$$\begin{aligned} s_k =& 2cos(A_k) \\ & \times \Big(cos(\frac{1}{2}\beta T_s^2) + jsin(\frac{1}{2}\beta T_s^2)\Big) s_{k-1} - s_{k-2}. \end{aligned} \tag{7}$$

Complex signal s_k can be represented by the real and imaginary terms. So we represent the complex signal s_k as follows:

$$s_k = a_k + jb_k, \tag{8}$$

where a_k is real part of s_k and b_k is imaginary part of s_k. We assume that $cos(\frac{1}{2}\beta T_s^2) \approx 1$ without loss of generality. Real part of complex signal s_k is only used. Therefore, signal can be modeled as follows:

$$a_k = 2cos(A_k)a_{k-1} - a_{k-2} \tag{9}$$

3 Robust Weighted Least Square Estimator

In this section, the RWLS is used to estimate the coefficients of the AR model. Transient equation can be defined as follows,

$$x_{k+1} = F_k x_k + w_k, \tag{10}$$

where $x_k \triangleq 2cos(A_k)$, F_k is transient matrix, and w_k is zero mean white Gaussian noise. We define stochastic signal $\tilde{a}_k$ before defining the measurement equation. The measured signal contains not only noise uncorrupted signal a_k but also noise signal. In order to represent the noise corrupted measurement signal, we denote as,

$$\tilde{a}_k = a_k + \bar{v}_k, \tag{11}$$

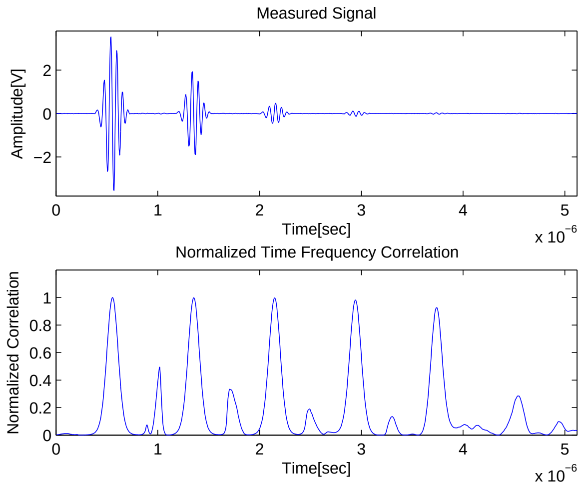

Figure 3: TFDR experiment on 10C-HFBT: 100m

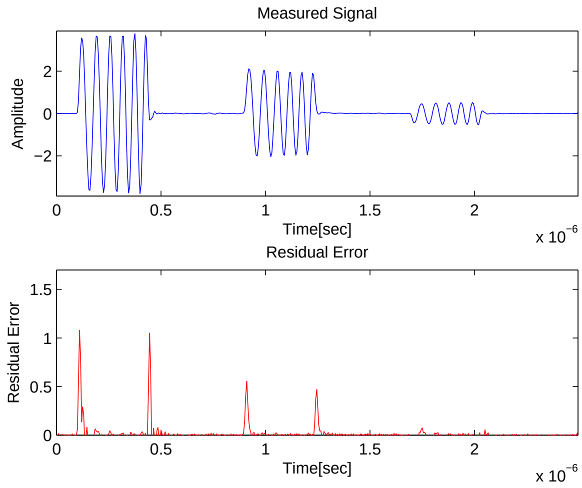

Figure 4: Proposed fault estimator experiment on 10C-HFBT: 100m

where $\tilde{a}_k$ is noise corrupted measured signal and $\bar{v}_k$ is zero mean white Gaussian noise. Equation(9) is rewritten as follows:

$$\tilde{a}_k + \tilde{a}_{k-2} = 2cos(A_k)(\tilde{a}_{k-1} - \bar{v}_{k-1}) + (\bar{v}_k + \bar{v}_{k-2}) \tag{12}$$

and then the measurement equation can be defined as follows,

$$y_k = [\tilde{H}_k - \Delta H_k]x_k + v_k, \tag{13}$$

where

$$y_k \triangleq \tilde{a}_k + \tilde{a}_{k-2}, \qquad v_k \triangleq \bar{v}_k + \bar{v}_{k-2},$$
$$\tilde{H}_k \triangleq \tilde{a}_{k-1}, \qquad \Delta H_k \triangleq \tilde{v}_{k-1}.$$

Measurement matrix $\tilde{H}_k$ is measured from sensor. We can only obtain measurement matrix $\tilde{H}_k$ that contains uncertainty. The RWLS estimator successfully eliminates the scale factor error and the bias error that is due to the stochastic uncertainty in the measurement matrix[3]. State-space equation can be obtained as follows:

$$x_{k+1} = F_k x_k + w_k,$$
$$y_k = [\tilde{H}_k - \Delta H_k]x_k + v_k.$$

It is assumed that the stochastic uncertainty ΔH_k is stationary, and ΔH_k and v_k are mutually uncorrelated in the RWLS.

$$E[\Delta H_k^T \cdot \Delta H_k] \triangleq \bar{R}_{k-1}, \tag{14}$$
$$E[\Delta H_k \cdot v_k] \triangleq 0,$$
$$E[\Delta H_k \cdot w_k] \triangleq 0.$$

The equations of RWLS are written as follows,

$$\mathcal{P}_{k|k}^{-1} = \lambda \mathcal{P}_{k|k-1}^{-1} + \tilde{H}_k^T \tilde{H}_k - \bar{R}_{k-1}, \tag{15}$$
$$\hat{x}_{k|k} = (I + \mathcal{P}_{k|k}\bar{R}_k)\hat{x}_{k|k-1} \tag{16}$$
$$+ \mathcal{P}_{k|k}\tilde{H}_k^T(y_k - \tilde{H}_k\hat{x}_{k|k-1}), \tag{17}$$
$$\mathcal{P}_{k+1|k} = F_k \mathcal{P}_{k|k} F_k^T, \tag{18}$$
$$\hat{x}_{k+1|k} = F_k \hat{x}_{k|k}. \tag{19}$$

where λ is the forgetting factor and $\mathcal{P}_{k|k}$ is the Gramian matrix. The existence condition of RWLS is given by,

$$\mathcal{P}_{k|k}^{-1} \triangleq (\mathcal{H}^k)^T \Lambda^k \mathcal{H}^k - (\Phi^k)^T \mathcal{R}^k \Phi^k > 0 \tag{20}$$

where Λ^k is the weighting matrix. The AR coefficient, $2cos(A_k)$, is estimated by the RWLS estimator.

4 Fault Distance Estimation via Residual

In this section, the fault distance estimation method via residual of the RWLS is presented. Not only the RWLS but also all estimator takes some time to converges at the true state. This is due to the convergence rate of estimator. If state is suddenly changed, residual is increased steeply. As the estimated state converges to the true state, residual is also decreased. We use this characteristics of estimator that residual is increased at the wide variation point of state to estimate the fault distance. In fault distance estimation, state is suddenly changed at the boundaries of the reference and the reflected signals. Residual has peak values at the boundaries of the reference and the reflected signals. Using the peak points of residual, fault distance is estimated. Residual can be defined as follows:

$$\begin{aligned} r_k &= y_k - \hat{y}_k \\ &= (\hat{a}_k + \hat{a}_{k-2}) - [\tilde{H}_k - \Delta H_k]x_k. \end{aligned} \tag{21}$$

5 Simulation Results

For the simulation, we use the linear chirp signal. In simulation, frequency range is $13 \sim 19.7$MHz, time duration is 340nsec, amplitude of the linear chirp signal is $6V_{pp}$, sampling rate is 200Msps and the length of cable is 100.08m. Velocity of propagation and noise standard deviation that are extracted from experiments are 2.502×10^8m/s, 0.013 respectively. Measured signal, true AR coefficients, and AR coefficient estimation are shown in Fig.1. In Fig.1, upper graph represents the measured signal. The first signal is the reference signal and the other signals are the reflected signals. Below graph represents the true AR coefficient by dotted line and estimation result by solid line. In Fig.1, true AR coefficient steeply changes at the boundaries of the reference and reflected signals. AR coefficient is properly estimated by the RWLS. However at the boundaries of the reference and reflected signal, estimation result does not follow the true AR coefficient. At the boundaries of the reference and reflected signals, residual will be steeply increased. This fact is shown in Fig.2. In Fig.2, below graph represents the residual. Peak locations of residual is coincident with the boundaries of the reference and reflected signals. The fault distance is computed by peak locations. In this simulation, estimated fault distance is 100.08m.

6 Experimental Results

In this section, the proposed fault distance estimator is compared with the conventional TFDR. Cable is 10C-HFBT 100m. Experimental set consists of arbitrary waveform generator(NI-PXI 5422), digital storage oscillator(NI-PXI 5124) and connector. Arbitrary waveform generater generates the Gaussian enveloped linear chirp signal that has the same time duration and frequency range of the linear chirp signal used in simulation. However, the Gaussian envelope is chirp signal. This reference signal flows with the conductor of cable via connector. The reference signal is reflected at the end of the cable that is open fault. Reflected signal is measured by digital storage oscilloscope.

In the same noisy environment, fault distance estimation is performed. The experimental results of TFDR and the proposed method are shown in Fig.3 and Fig.4. The fault distance of TFDR is 100.07m and the proposed method gives the fault distance as 100.08m. From these results, proposed estimator offers reliable estimation results. The Proposed fault distance estimator reduces the computational burden of TFDR because the proposed estimator uses the RWLS and residual instead of cross correlation and joint time-frequency energy distribution. Therefore the proposed fault distance estimator is suitable to real-time implementation.

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References

[1] Y. J. Shin, J. Powers, T. S. Choe, C. Y. Hong, E. S. Song, J. G. Yook, and J. B. Park, "Application of Time-Frequency Domain Reflectometry for Detection and Localization of a Fault on a Coaxial Cable", *IEEE Transactions on Instrumentation and Measurement*, Vol. 54, No. 6, Dec. 2005.

[2] W. S. Ra, I. H. Whang, and J. B. Park, "Robust Weighted Least Squares Range Estimation for UAV Applications", *SICE Annual Converence 2008*, pp. 251-255, Aug. 2008.

[3] G. H. Choi, W. S. Ra, T. S. Yoon and J. B. Park, "Low-Cost Tachometer based on the Recursive Frequency Estimation for Automotive Applications", *SICE Ann. Conf.*, pp. 46-49, Sep. 2007.

[4] R.J Vaccaro,C.S Ramalingam, D.W.Tufts, R.L.Field "Least-squares time-delay estimation for transient signals in a multipath environment",*J.Acoust.Soc.Am* Vol. 92, No 1, pp.210-218, July 1992.