

ADAPTIVE POWER-LINE DISTURBANCE DETECTION SCHEME USING A PREDICTION ERROR FILTER AND A STOP-AND-GO CA CFAR DETECTOR

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ABSTRACT

This paper presents a new power-line disturbance detection algorithm. The utilized recursive least square (RLS) prediction error filter extracts the power-line disturbance signal from recorded data, and the modified stop-and-go cell average constant false alarm rate (CA CFAR) detector makes a decision based on the squared output of the previous stage. The detection performance of the proposed algorithm is determined by simulations, and actual high voltage transmission line data is utilized to demonstrate the performance of the proposed algorithm.

1. INTRODUCTION

Good electric power quality has become an important issue over the past several years at both the distribution and transmission level [1]. Voltage sagging is the one of the most important disturbances in both types of systems, and is one of the principal disturbances of interest at the transmission level.

Two of the most important features of voltage sag to be identified include accurate determination of the time at which the voltage sag begins and ends. The current state of art in analyzing sagging of power-line voltages is the root mean square (RMS) method, and the starting time and ending time of sagging is measured by this method. However, this may not give precise time information regarding the beginning and ending of sagging events, since it has up to one cycle error per sagging event [2]. This is due to the fact that the RMS value is calculated over the period of one cycle. In addition, too much disturbance data are collected on a modern-day high voltage transmission system to be analyzed by humans. Thus there is a need to “automatically” detect voltage sag events and to accurately determine their beginning and ending times.

In this paper we present a new voltage sag detection algorithm to detect sagging automatically, and to determine its starting and ending time more exactly. The proposed

algorithm consists of an adaptive prediction error filter and a stop-and-go CA CFAR detector which is a newly modified algorithm of the CA CFAR detector.

This paper consists of three sections. In Sec. 2, we present a power-line disturbance signal model, the adaptive prediction error filter, and the proposed stop-and-go CA CFAR detector. Sec. 3 contains the experiments and results using simulation and actual high voltage (138 kV) transmission line data. Finally, Sec. 4 concludes the paper.

2. ADAPTIVE POWER DISTURBANCE DETECTION ALGORITHM

The adaptive power-line disturbance detection scheme is shown in Fig. 1, and is composed of the power-line disturbance signal model, an adaptive prediction error filter, and a new proposed stop-and-go CA CFAR detector.

2.1. Power-line Signal Model

Most steady-state power-line signals consist of a fundamental frequency, e.g., 50 Hz or 60 Hz, several harmonics with relatively small amplitudes, and noise. To this steady state, transient disturbance events are sporadically added. In this paper we are concentrated with voltage sag events. In this case the signal has four factors : the fundamental sine wave of the power-line signal, harmonics, noise which is assumed to be zero-mean Gaussian noise, and the voltage sag disturbance signal. Except for the power line fundamental and its harmonics, all these factors are assumed orthogonal to each other in that every factor occurs independently and their cross-correlations are zero. Therefore, we can build up the discrete power-line disturbance signal with sampling rate $2f_N$ as follows.

$$x(n) = a \sin(\omega_0 n + \theta) + \sum_{k=2}^l a_k \sin(k\omega_0 n + \theta_k) + s(n) + g(n) \quad (1)$$

where $\omega = 2\pi f_0$, ($f_0 = 50$ Hz or 60 Hz), and θ, θ_k are phases in $[-\pi, \pi)$, and $lf_0 < f_N$, and $a \gg a_k$ for all integers $k \in [2, l]$, and $s(n) =$ disturbance signal if it occurs, and $g(n) =$ additive Gaussian noise with zero mean and σ^2 variance. This model is the basis of the new detection algorithm, and agrees well with the real system. Unfortunately,

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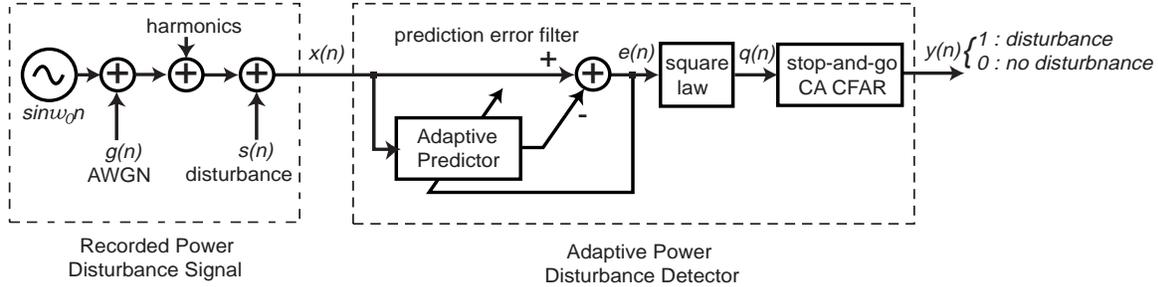


Figure 1: Power line sag disturbance signal modeling and detector block diagram

however, the variances of the noise and disturbance signal are unknown.

2.2. Adaptive Prediction Error Filter

To detect the power-line disturbance $s(n)$ from Eq. (1), if the basic signal is only one sine wave at either 50 or 60Hz, a band rejection filter can be applied ; however, due to the presence of harmonics which vary with time and load conditions, an adaptive filter is required to extract only the disturbance signal.

In this paper an adaptive prediction error filter is utilized because of its orthogonality characteristics between input and output values. Therefore the correlated signal, e.g., fundamental sine wave and its harmonics, in the power-line signal can be eliminated.

Among several possible adaptive prediction error filters, this paper utilizes the recursive least-squares (RLS) filter [3], which is simple and robust.

Since the ω_o frequency signal and its harmonic signals are assumed orthogonal to $s(n)$ and $g(n)$, the output $e(n)$ of the prediction error filter can be approximated as

$$e(n) \approx s(n) + g(n) \quad (2)$$

2.3. Proposed Stop-and-Go CA CFAR Detector

The detection of the power-line sag disturbance signal $s(n)$ problem can be changed into a signal detection problem in Gaussian random noise through an adaptive prediction error filter. Thus, the main concern of the disturbance detector is to detect the disturbance signal $s(n)$ from Eq. (2). To analyze this problem completely we need true *a priori* probability density function (pdf) of $s(n)$ and $g(n)$. However, only the distribution of noise $g(n)$ is known (actually assumed) as zero mean Gaussian ; however, its variance is unknown. Furthermore, the mean and variance of the disturbance signal $s(n)$ are unknown as well. When a restriction which maximizes detection probability for a constant false alarm rate is used, the cell averaging (CA) constant false alarm rate (CFAR) detector can be utilized in that it is an optimal detector if the input has an exponential probability density function (pdf) [4]. For this reason, square law processing is executed at the output of the prediction error filter as indicated in Fig. 1. Thus, for the noise-only case, the output of prediction error filter, $e(n)$, is changed simply to $q(n) = |e(n)|^2$, and the output distribution of

this processing has changed from Gaussian to exponential distribution [5].

In the CA CFAR algorithm, in order to detect the signal in noise, every test cell is compared to the threshold (THR) which is obtained from the multiplication of the estimated local noise mean and the constant T derived from a false alarm rate.

The main concern of the CA CFAR detector is to estimate the true noise mean. Thus, in this paper we propose a *new* modified version of the CA CFAR detector based on the following two changes : first, removal of left-side cells used in the calculation of the noise mean, and second, “stop-and-go” processing when the data are saved in the right cells q_1, \dots, q_N shown in Fig. 2.

Since the RLS prediction error filter is a finite impulse response (FIR) filter of length M, and even though only one sample of the power-line disturbance signal may exist, the output of this filter $e(n)$ will be of length M and of amplitude greater than the background noise. For this reason, when a test cell $q(0)$ at time 0 is greater than a threshold, the following M data are expected to have “large” values, thus “stopping” movement to the right, i.e., stopping movement to the N averaging cells q_1, \dots, q_N , in Fig. 2. In other words, these samples are not regarded as background noise. In addition, the sag disturbance in power-line signals occurs within less than one cycle of the fundamental frequency. In this paper, the blocking data length L in Fig. 2 is set to the same length M of the prediction error filter. On the other hand, if a sample value at time 0 is not larger than the threshold, the test cells in this case “go” to the averaging cells. This stop-and-go CA CFAR detector is shown in Fig. 2.

Through the square law processing, $s(n)$ and $g(n)$ are changed into the squared values, e.g., $\hat{s} = |s(n)|^2$ and $\hat{g} = |g(n)|^2$. Let the $q(n)$, $\hat{s}(n)$ and $\hat{g}(n)$ be denoted by the random variables (RV) q , \hat{s} , and \hat{g} to simplify the notation. Then, the following hypothesis can be defined as

$$H_0 : q = \hat{g} \quad (3)$$

$$H_1 : q = \hat{s} + \hat{g} \quad (4)$$

where $E(g) = \mu$, and the RV q for H_0 and H_1 have exponential distribution and their *a priori* pdfs [6] which are defined by

$$p(q|H_0) = \frac{1}{\mu} e^{-q/\mu} \quad (5)$$

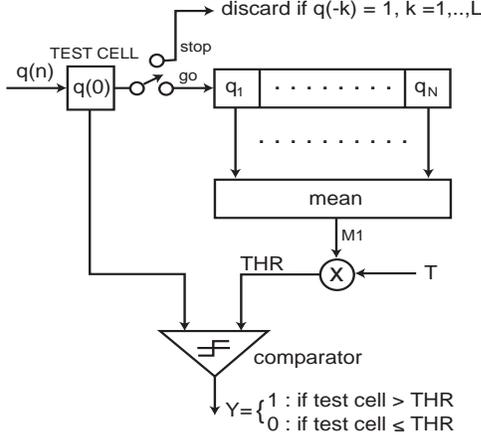


Figure 2: Stop-and-go CA CFAR detector block diagram

$$p(q|H_1) = \frac{1}{(1 + SNR)\mu} e^{-q/(1+SNR)\mu} \quad (6)$$

respectively, and where SNR denotes signal to noise ratio.

The real CFAR detector uses the estimated mean since μ is unknown, therefore the probability of the false alarm is defined as

$$P_{FA} = \int_0^{\infty} P(q > T * M1|H_0) p_{M1}(q) dq \quad (7)$$

and the probability of the detection is given by

$$P_D = \int_0^{\infty} P(q > T * M1|H_1) p_{M1}(q) dq \quad (8)$$

where $p_{M1}(q)$ is the pdf of the noise mean RV $M1$. If the true mean value $M1$ is estimated, $p_{M1}(q)$ becomes $\delta(q - \mu)$ for the no disturbance case and $\delta(q - (1 + SNR)\mu)$ for the disturbance case. Therefore, in the ideal case P_{FA} and P_D in Eq. (7) and (8) are defined as

$$P_{FA} = e^{-T} \quad (9)$$

$$P_D = e^{-T/(1+SNR)} \quad (10)$$

3. EXPERIMENT AND RESULT

In this paper we utilize voltage sag data actually observed on a 60 Hz, 138 kV high voltage transmission line. The sampling frequency is 3,840 Hz.

Before testing the actual data, we investigate the performance of the RLS prediction error filter and a stop-and-go CA CFAR detector.

3.1. Performance Check

For the RLS prediction error filter, the performance can be measured by the convergence speed and the extraction ability of the non-correlated signals. The initial value of the weighting matrix \mathbf{W} of the RLS filter is set equal to zero, and selected number, M , of taps is 16. With these parameters the convergence level of the RLS filter was reached

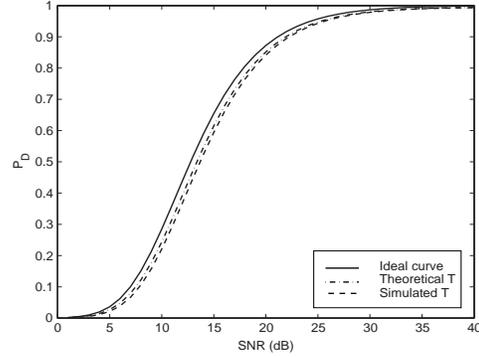


Figure 3: The performance of detection probability P_D vs. $SNR(dB)$ with ideal, and theoretical constant T , and simulated constant T cases.

in 10 iterations. In this simulation, the 16-tap weighting vector length turns out to be a good choice for the RLS filter. This is because when the power-line voltage sag takes place the voltage drops in less than a cycle, which consists of 64 samples in the field test data presented in the next section. Therefore, the start of the sag “steady state” can be detected by the filter. Similarly, it can detect the end of the sag, e.g., the recovering state of the fault.

Another main concern of this adaptive prediction error filter is to extract the disturbance signal from the power-line disturbance data. For this simulation we generated a 10000 sample sinusoidal signal at 60 Hz with a 3840 Hz sampling rate, with 3rd and 5th harmonics with 1/10 and 1/50 amplitudes, respectively, and zero-mean Gaussian noise with SNR 80 dB. One hundred independent experiments were conducted. By this simulation, the output of the RLS prediction error filter consisted of only noise and its distribution is well fitted by a Gaussian.

The proposed stop-and-go CA CFAR detector performance is measured by the detection probability related to the SNR. If the noise mean has a δ function, the constant T can be calculated from Eq. (9) for a given false alarm rate, and its performance can be derived from Eq. (10). However, if the background noise mean distribution does not correspond to the ideal case, e.g., not a δ function, the mean should be calculated from local data with length N , and its theoretical performance can be calculated from Eqs. (7) and (8). In this non-ideal case, the theoretical constant T related to the false alarm is given by [4, 6]

$$T = N(P_{FA}^{-1/N} - 1) \quad (11)$$

where N is the number of cells which are used for the calculation of the background noise mean, $M1$ in Fig 2. However, practically speaking, the false alarm rate with this theoretical constant T is not the same as we set. Therefore, we need to find the new constant T by the simulation. To obtain this constant T , 10000 zero-mean Gaussian distributed samples followed by the square law processing were executed 100 times independently.

In this paper the length of the averaged cells, N , is set equal to 64 to obtain of one cycle of the power-line signal

local noise mean value. This length is larger than most CFAR detectors used in radar. To obtain a $P_{FA} = 10^{-6}$ with 64 averaging cells, the theoretical value of constant T by Eq. (11) is 15.42, and by the experiment it is 16.51. The performance of each is shown in Fig. 3 : For the ideal case the performance is plotted as solid line, and for the non-ideal case the theoretical constant T as a dash-dot line, and simulated constant T as a dash line.

From this figure, the CFAR loss, which is defined as the difference between the SNRs of the ideal and real cases at $P_D = 0.5$, is 0.65dB and 0.95dB, respectively. These losses are smaller than other CFAR detectors due to the large value of average window length. When the length of this window, N , is larger, the CFAR loss decreases.

3.2. Application to Actual Sag Data

We have used this adaptive detection scheme to identify the beginning and ending of several voltage sag disturbance events. In Fig. 4 we present a typical result for high-voltage transmission lines. This data was recorded with 3840 Hz sampling rate in Texas in 1997. It is a phase B signal among three phases and its RMS voltage is 138 kV. The amplitude of the data shown in Fig. 4 is normalized. The horizontal-axis used in Figs. 4 (a) (b) (c) is the sampling index and its scale can be mapped from 0 to 0.26 second. Thus the voltage sag is initiated over a very short period of time.

The normalized actual sag disturbance data is shown in Fig. 4 (a), and 17% voltage drop , i.e., sag, takes place over 5 cycles. Fig. 4 (b) shows the output $q(n)$ of square law processing whose input is the output $e(n)$ of the prediction error filter as indicated in Fig. 1. Note that in this figure, the vertical-axis has a log scale. As shown in this figure the local noise mean is not a constant, but varies. To calculate the constant T we selected 10^{-6} for P_{FA} . As a result of the tests described previously, the constant T was selected to be 16.51 by the simulation. The threshold THR, formed by multiplying the result of the local noise mean and the constant T, is shown in the same figure. This THR value also changes adaptively with the variation of the background noise mean. The time at which $q(n)$ exceeds the threshold THR denotes the occurrence of a disturbance.

The output of this algorithm Y is plotted in Fig. 4 (c) as 1 (the test cell is larger than THR) or 0 (the test cell is not larger than THR). By examining this figure, we can determine the starting and ending times of sagging, e.g., in the first detected group the very first one indicates the the start of the disturbance, and in the second detected group the last one indicates the end of the disturbance. Their time indices are 272 and 719, respectively. If we change them to time they map to 0.071 second and 0.1872 second, respectively. Thus the sag disturbance duration is 0.1162 second.

4. CONCLUSIONS

In this paper a detector with an adaptive prediction error filter and new stop-and-go CA CFAR detector is shown to accurately detect the power-line sag disturbance signal. This scheme gives precise time information regarding the starting and ending times, while current commercial RMS

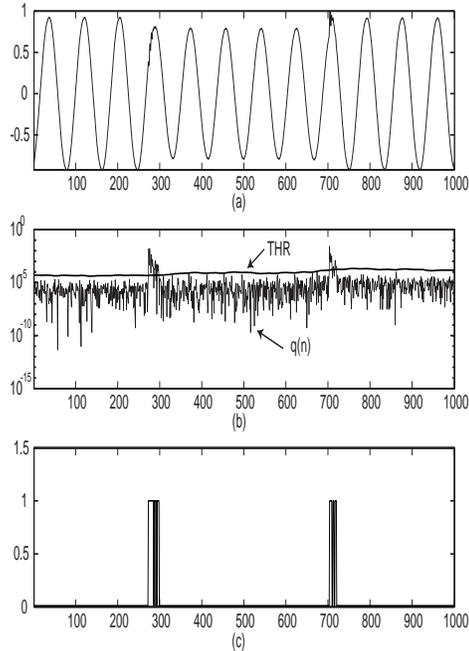


Figure 4: An adaptive power-line disturbance detector result example, (a) power-line disturbance (sag) signal, (b) adaptive prediction filter output, $q(n)$ and stop-and-go CA CFAR detector threshold, (c) stop-and-go CA CFAR detector output

detectors are quite limited in this respect. Future work will involve investigating the effects of changing the probability of false alarm P_{FA} on the performance of the sag detector. To do this we will utilize a data base of voltage sag events observed on high voltage transmission lines.

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