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# Wavelet De-Noising for Power Quality Event Detection

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## ABSTRACT

The noise in a power signal degrades the detection rate of the power quality (PQ) event signals. We present a new wavelet de-noising technique for PQ event detection that employs the correlation-based thresholding instead of the wavelet-scale-based thresholding of existing schemes. The simulation results show that the proposed scheme is more robust to Gaussian and impulsive noisy conditions and has further improved detection ratio than existing schemes.

**Key Words** : Power Quality (PQ), PQ Event Detection, De-noising, Wavelet, Wavelet Correlation

## Ⅰ. Introduction

A discrete wavelet transform (DWT) is well-known to be simple but good for de-noising. Recently, many studies[1-3] have been presented on wavelet de-noising techniques. The authors in Ref. [4] first suggest a de-noising technique that uses the spatial correlation between adjacent scales to detect PQ events in low signal-to-noise ratio (SNR) channels.

In this Letter, we introduce a new wavelet de-noising technique using correlation-based thresholding, where a modified Donoho's universal threshold that is a function of correlation is defined. The power signal could be corrupted by impulsive noise due to power switch ON/OFF as well as by Gaussian noise. However, in our literature search, existing techniques have not been evaluated over impulsive noise conditions yet. Hence, we first evaluate the presented de-noising procedure over both Gaussian and impulsive noisy channels and compare to existing schemes. We implement the Bernoulli Gaussian model to generate Gaussian plus impulsive noise samples[5]. In that model, the noisy power line (or received) signal $x_n$ is represented as

$$x_n = s_n + n_n + i_n = s_n + w_n, \tag{1}$$

where $s_n$ are the power event signal samples, $n_n$ the Gaussian noise samples with variance $\sigma_G^2$, and $i_n$ the impulsive noise samples with variance $\sigma_I^2$.

For the proposed de-noising algorithm, we decompose the input signal $x_n$ using DWT, calculate the correlation between the adjacent detail wavelet coefficient (WC) scales, and then update those scales via thresholding and noise removal processes. For instance, Fig. 1 shows the de-noising process for a noisy sag signal input $x_n$ (Fig. 1(a)), where a sag component of 0.9 *pu* (per unit) & 2 cycles (when considering critical PQ conditions[6]) is added to the original 60Hz power signal. Assume that the sampling rate is 15360 points/s (i.e., 256 per cycle), the number of all scales $M$ = 8, and the

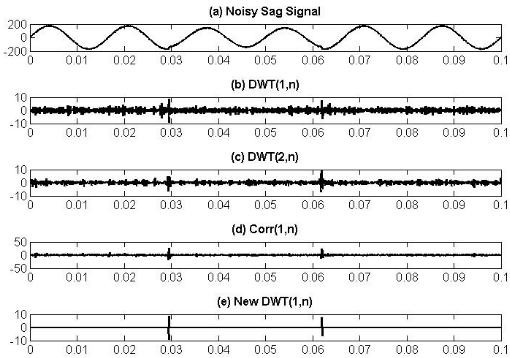


Fig. 1. De-noising of a noisy sag signal

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SNR = 35dB.

In the following, we explain a DWT-based noise removal algorithm using spatial correlation which corresponds to scale inter-multiplication operation between adjacent WCs ( • denotes the scale inter-multiplication operator)[4].

**Step 1**: Calculate the correlation coefficients with the adjacent WC scales:

$$Corr_k(m,n) = \prod_{i=0}^{k-1} DWT(m+i,n), \tag{2}$$

where $m\,(< M-k+1)$ and $n\,(=1,2,...,N)$ are the scale (or dilution) and time-shift (or translation) indices, respectively, and $k\,(\geq 2)$ is the size of adjacent scales that are correlated. For instance, for $k=2$ and $m=1$, the wavelet correlation for a noisy input signal $x_n$ results in

$$Corr_2(1,n) = DWT_x(1,n) \bullet DWT_x(2,n). \tag{3}$$

The correlation (see Fig. 1(d)) represents the two edge points due to the PQ disturbance more clearly than the wavelet scales $DWT_x(\cdot\,,n)$ (see Fig. 1(b), (c)), as compared to noise samples. Hence, in this Letter, we use the correlation coefficients instead the wavelet-scale coefficients that existing schemes[4] choose for the threshold decision (as explained the next step).

**Step 2**: Define the threshold value $THR(m)$ for the noise removal. In our scheme, we modify the Donoho's universal threshold[7] with a standard deviation $\sigma_{SD}$ that is a function of the correlation as follows:

$$\sigma_{SD}(m) = \left\{median\left(|Corr_k(m,n)|\right)/(.6745)^{ak}\right\}^{\frac{1}{k}}. \tag{4}$$

Table 1 shows the statistically-evaluated (and selectively chosen) false alarm rate $P_{fa}$ and miss detection rate $P_{md}$ for different combinations of $\alpha$ and $k$ in (4) (resulting in a different threshold) in the presence of pure Gaussian noise ($i_n = 0$ in (1)) or impulsive noise ($i_n \neq 0$ in (1)), in order to estimate an optimal (or near-optimal) threshold. Assume that $P_{fa}$ < 0.5%, $P_{md}$ < 2% are requested for Gaussian noise, and $P_{fa}$ < 1.5%, $P_{md}$ < 2% are requested for impulsive noise. From Table 1, we may choose $\alpha$ = 3 & $k$ = 3 (the best case) or $\alpha$ = 3 & $k$ = 2 (the second best case) to satisfy the given requirements. In Table 1, we can confirm that the correlation-based thresholding of the proposed scheme is better than the wavelet-scale-based thresholding of the existing scheme[4] (for which $P_{fa} \cong 1\%$, $P_{md}$ = 4.12% are evaluated).

Table 1. Statistical false alarm and miss detection rate

| $k$ | $\alpha$ | $P_{fa}(\%)$ | | $P_{md}(\%)$ | |
|---|---|---|---|---|---|
| | | $n_n$ | $i_n$ | $n_n$ | $i_n$ |
| 2 | 1 | 2.5 | 4.3455 | 0 | 0 |
| | 2 | 0.6 | 2.5420 | 0.04 | 0 |
| | 3 | <0.08 | 1.2459 | 0.98 | 0.22 |
| 3 | 1 | 2.2 | 3.2910 | 0 | 0 |
| | 2 | 0.4 | 1.7840 | 0 | 0 |
| | 3 | <0.05 | 0.7645 | 0.2 | 0.12 |
| Existing[4] | | $\cong 1$ | N/A | 4.12 | N/A |

**Step 3**: Assign the masking value $MASK(m,n)$ through a comparison of the threshold value $THR(m)$ and $|Corr_k(m,n)|$ ; i.e., if $|Corr_k(m,n)|$ is less than $THR(m)$, the masking value is 0; otherwise it is 1:

$$
\begin{aligned}
& MASK(m,n) = 0; \\
& For\, m = 1:M \\
& \quad For\, n = 1:N \\
& \quad\quad If\ |Corr_k(m,n)| \geq THR(m) \\
& \quad\quad\quad MASK(m,n) = 1 \\
& \quad\quad End \\
& \quad End \\
& End
\end{aligned}
$$

**Step 4**: Determine the new wavelet scales $\widehat{DWT}_x(m,n)$ as follows:

$$\widehat{DWT}_x(m,n) = MASK(m,n) \bullet DWT_x(m,n).$$

The new scales that suppress noise components (see Fig 1(e)) clarify the starting and ending edges of the disturbance.

**Step 5**: Apply the inverse discrete wavelet transform (IDWT) to all the new scales obtained in Step 4 such that the recovered signal can be obtained.

We implement the proposed algorithm using Matlab and apply it to various noisy PQ events, including sag, swell, interruption, harmonics, and transient events, via a Gaussian noise channel. In simulation, as the mother wavelet, we choose Daubechies 8 (db8). The threshold is set to the case

$\alpha$ = 3 & $k$ = 2 rather than the case $\alpha$ = 3 & $k$ = 3 considering comparable hypothetical testing results as well as algorithm simplicity. The detection rate is calculated by averaging the sample results at different cycles. From Table 2, we observe the detection rate and recovered SNR gain $\eta$ (=$\eta_{output}$ [recovered SNR] $- \eta_{input}$[input SNR]) of the proposed scheme and compares it to the one of the existing scheme in Ref. [4] (see the bracket ( ) in Table 2).

Table 2 shows that the proposed scheme improves the detection rate, especially at low SNR ($\leq$40dB), when compared to the existing one[4]. It also shows that $\eta$ of the presented scheme is improved.

We simulate various PQ events over impulsive noise channels, for which the two impulsive noise parameters are set $\mu = 5$, $\psi = 0.5$[5]. The results in Table 3 confirm that the proposed scheme is superior to the conventional scheme (see ( ) in Table 2) even at the impulsive conditions.

Table 2. PQ event detection ratio and recovered SNR gain over Gaussian noise

| SNR(dB) | | Detection Rate | | | | |
|---|---|---|---|---|---|---|
| $\eta_{input}$ | $\eta_{output}$ | Sag | Swell | Interru-ption | Harm-onics | Trans-ient |
| 40 | 45.4 | 100 (98) | 100 (97) | 100 (100) | 100 (97) | 100 (100) |
| 35 | 40.1 | 100 (96) | 98 (94) | 100 (100) | 100 (95) | 100 (100) |

Table 3. PQ event detection ratio and recovered SNR gain over impulsive noise

| SNR(dB) | | Detection Rate | | | | |
|---|---|---|---|---|---|---|
| $\eta_{input}$ | $\eta_{output}$ | Sag | Swell | Interru-ption | Harm-onics | Trans-ient |
| 40 | 44.5 | 100 (97) | 100 (95) | 100 (96) | 100 (98) | 100 (97) |
| 35 | 40.4 | 100 (93) | 98 (90) | 100 (98) | 100 (96) | 100 (98) |

## Ⅱ. Conclusion

In this Letter, we have proposed a new wavelet de-noising technique using correlation-based thresholding. The proposed scheme has improved the detection rate of various PQ events compared to existing schemes over Gaussian and impulsive noisy environment.

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