Comparison of Various De-Noising Algorithms pertaining to Power Quality Signals using Phaselet Transform

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Abstract:-Various wavelet-based noise reduction methods discussed here are replaced by the Phaselet transform for decomposition and reconstruction of the signal. First, we improve the traditional spatially selective noise filtration technique proposed by Xu et al. Second, we introduce a new threshold based denoising algorithm based on undecimated discrete wavelet transform using PT. And finally an algorithm Known has Stein's Unbiased Risk Estimator (SURE) which has been used for denoising for Musical signals has been applied in this paper for power signals. Simulations and comparisons are given along with the values of SNR pertaining to the above algorithms for different waveforms.

Key-words:- Spatially Selective Noise Filtration, Orthogonal Phselet transform, SURE, UDPT, Phaselet Transform, Denoising.

1. Introduction

Due to the increasing popularity of power electronics, power quality (PQ) related disturbances in power systems have become one of the major concerns of utility companies and commercial customers. PQ problems significantly affect many industries, particularly semiconductor industry, ecommerce, chemical industry, automobile industry, and paper manufacturing. A report by CEIDS (Consortium for Electric Infrastructure to Support a Digital Society) shows that the U.S. economy is losing between $15 billion to $24 billion due to PQ phenomena. To detect, solve, and prevent power quality problems, many utilities perform power quality monitoring for their industrial and key customers. Deregulated industries face increasing competition, the power quality monitoring would be an effective means for providing customer services and for reinforcing competitiveness of the utilities. To improve power quality the transients must be detected and classified before mitigating action takes place. However, its capabilities are often significantly degraded owing to the existence of noises riding on the signal [1]. In particular, as the spectrum of the noises coincides with that of the transient signals, the effects of noises cannot be excluded by means of some kinds of filters without affecting its performance.

What remains to be solved for the method is to overcome the difficulties of capturing the disturbance signals out of the background noises in a low signal/noise ratio (SNR) environment and to restore the performance, as if we were processing "pure" signals.

2. Conventional Transforms used for Denoising

The Fourier transform (FT) has been used as an analyzing tool for extracting the frequency contents of the signals recorded. According to the frequency contents of the signals, some of the PQ problems can be detected. Nevertheless, with constant bandwidth, the FT is not so efficient as to capture the short-term transients.Besides, the time-evolving effects of the frequency in non-stationary signals are not considered in the FT techniques. Although the short-time Fourier transform (STFT) can partly alleviate the problem, the STFT still has the limitation of a fixed window width, which means the Trade-off between the frequency resolution and the time resolution should be determined a priori to observe a particular characteristic of the signals. The limitation of a fixed window width in fact is inadequate for the analysis of the transient non-stationary signals. To improve the effectiveness of the FT, many researchers have proposed the use of the WT approach to analyzing the power system disturbances. One of the fundamental problems using wavelet transform is the lack of shift invariance of the total energy in the transform coefficients at a particular scale. So by taking the Fourier transform of n – redundant wavelet transform having fixed magnitude and fixed phases that are related to each other in a redundant way and hence the transform would be approximately shift invariant.

2.1 Phaselet Transform

A set of functions $\left\{\psi_1^l\right\}_{l=0}^{n-1}$ is called a strict Phaselet family if their Fourier transforms are of the form

$$\psi_1^l(\omega) = \psi_1^l(\omega) e^{i\theta^l(\omega)} \quad (1)$$

Where ψ_l generates a frame for $L^2(R)$,

$$\theta^l(\omega) = -\pi\tau^l sign(\omega),\ \tau^l \in R. \quad (2)$$

The number of Phaselets n in a Phaselet family is called the redundancy of the Phaselet family. We take into account a three-redundant canonical Phaselet family with two vanishing moments. The plot of Phaselet & Scaling functions are given below with *n* = 3, *K* = 2 and *L*=6.

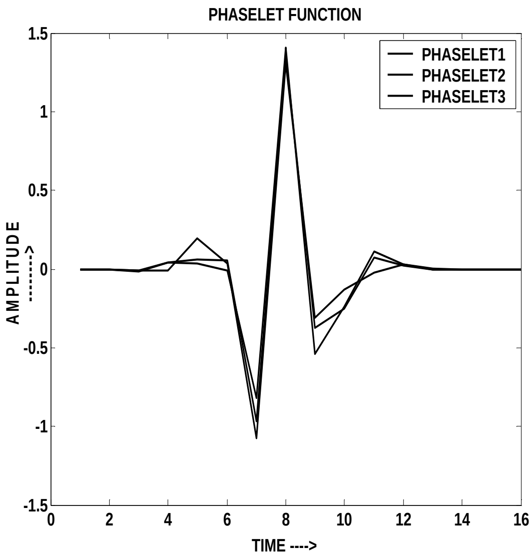

Fig.1 Phaselet Function

The Phaselet Transform (PT) approach prepares a window that automatically adjusts to give proper resolutions of both the time and the frequency [2]. In this approach, a larger resolution of time is provided to high-frequency components of a signal, and a larger resolution of frequency to low-frequency components. These features make the PT well suited for the analysis of the power system transients caused by various disturbances.

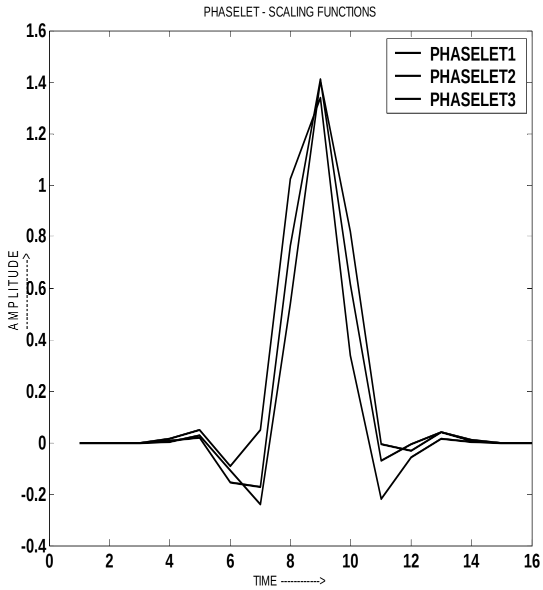

Fig.2 Scaling Function

This paper proposes various de-noising scheme to be integrated with the PT as a part of the PQ monitoring system. Based on the PT and the de-noising techniques, the developed system is equipped with the abilities of detecting and localizing (in time) the occurrence of the power disturbances in the noisy surroundings. Let the noise-corrupted signal monitored by the PQ monitoring system be defined as an empirical signal. Without loss of generality, suppose the noises riding on the signals during measurement and/or communication are a random process of the stationary white Gaussian distribution and can be added to the input transient signals to emulate the noise-corrupted signals:

$$x_n' = x_n + N_n(0, \sigma^2) \quad (3)$$

Where

x_n - is the pure nth sampled signal without noise

$x_n^{'}$ - is the empirical signal corrupted by the noise $N_n(0,\sigma^2)$

$N_n(0,\sigma^2)$ - represents a Gaussian random Variable sampled at time with the mean zero and the Standard Deviation σ.

To eliminate impacts of the noises on detection of the disturbance, a threshold value can be employed to approximate the effects of the random noise $N_n(0,\sigma^2)$, n=1.

3. Denoising Algorithms

3.1 Spatially Selective Noise Filtration (SSNF)

Xu *et al.* developed a SSNF technique that used the dyadic wavelet constructed by Mallat [3]. In this paper the conventional wavelet transforms which where used for denoising have been replaced by Phaselet transform due to the increased number of coefficients. Based on the fact that sharp edges have large signals over many wavelet scales and noise will die out swiftly with scale, spatial correlation $Corr_l(m,n)$ is defined to sharpen and enhance edges and significant features while suppressing noise and small sharp features.

$$Corr_l(m,n) = \prod_{i=0}^{l-1} P(m+i,n) \qquad (4)$$

$$n = 1,2,....N$$

Where $P(m,n)$ denotes the Phaselet transform data, m is the scale index, n is the translation index, $l < M - m + 1$ and M is the total number of scales. The algorithm is described briefly as follows. The filtered data is referred to as $P_{new}(m,n)$:

Step:1 Compute the correlation for Phaselet Coefficient $P(m,n)$

Step:2 Rescale the power of $\{Corr_l(m,n)\}$ to that of $\{P(m,n)\}$ and get $\{NewCorr_l(m,n)\}$.

$$NewCorr_l(m,n) = Corr_l(m,n)\sqrt{PP(m)/PCorr(m)} \qquad (5)$$

Where

$$PCorr(m) = \sum_n Corr_l(m,n)^2 \qquad (6)$$

$$PP(m) = \sum_n P(m,n)^2 \qquad (7)$$

Step:3 If $|NewCorr_l(m,n)| \geq |P(m,n)|$ we Accept the point as an edge. Pass $P(m,n)$ to $P_{new}(m,n)$ and reset $P(m,n)$ and $Corr_l(m,n)$ to 0. Otherwise, we assume $P(m,n)$ is produced by noise and then retain $P(m,n)$ and $Corr_l(m,n)$.

Step:4 Repeat 2) and 3) until the power of $P(m,n)$ is nearly equal to some reference noise power.

The plot corresponding to the SSNF using Phaselet transform is given below for block and Heavisine signals

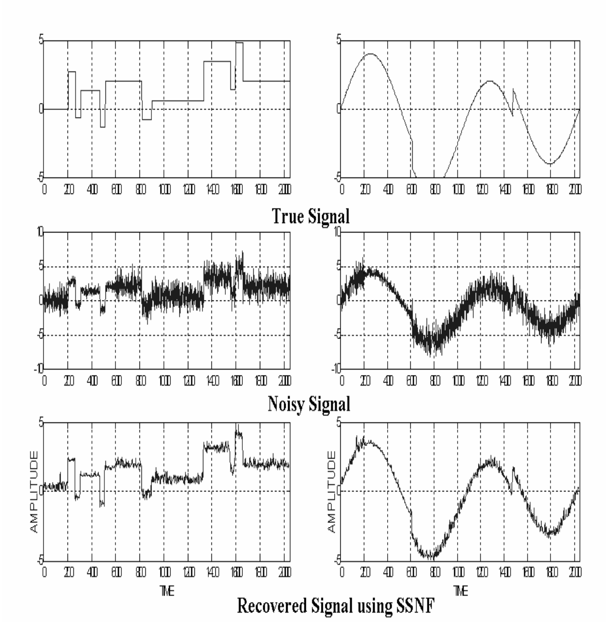

Fig.3 a) Blocks b) Heavisine

The edges will appear at all scales; therefore, we can assume that if there is no edge to be extracted at coarser scales, then we will not extract edge at finer scales at the corresponding indexes. Thus, we will extract edges from coarser scales to finer scales only at the indexes that have been extracted as edges. This will avoid extracting a lot of noise as edges at fine scales.

3.2 Orthogonal Phaselet Transform

Donoho first proposed threshold-based denoising [3]. It is very simple and of satisfying performance. It can be divided into three steps:

- Transform the noisy signal y into Phaselet coefficient P.
- Employ a hard or soft threshold t.
- Transform back to the original domain, and get the estimated signal.

In case of orthogonal wavelet transform (OPT), Donoho gave the following soft threshold:

$$\eta_t\left(\omega\right) = \operatorname{sgn}(\omega)(|\omega - t|) \quad (8)$$

$$t = \sigma\sqrt{2\log N} \quad (9)$$

ω – Phaselet Coefficients; σ - Standard deviation; N- Length of the signal.

The plot corresponding to the OPT using Phaselet transform is given below for block and Heavisine signals.

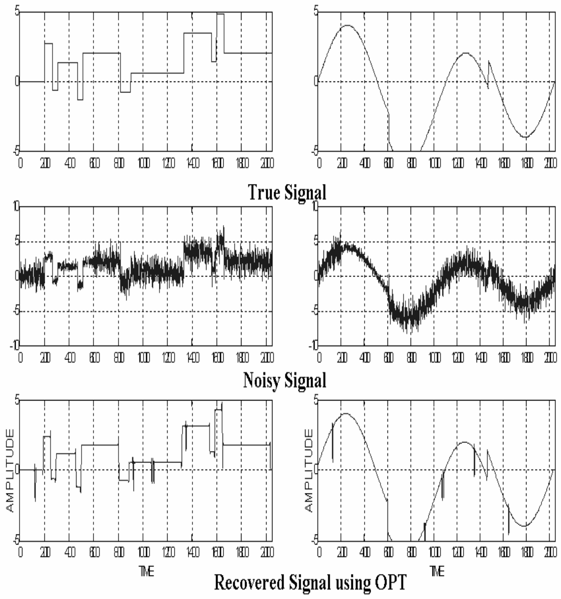

Fig 4 a) Blocks b) Heavisine

3.3 Undecimated Phaselet Transform

Lack of a translation invariant will make denoising by OPT exhibit visual artifacts. In this correspondence, we describe UDPT and hard threshold [3]. Although Donoho proved the optimality of soft threshold in theory, hard threshold has shown better results for certain applications.

$$P(m,n) = \begin{cases} P(m,n) & P(m,n) \geq t(m) \\ 0 & P(m,n) < t(m) \end{cases} \quad (10)$$

If we use SNR as the measure of filtering performance, we can see that UDPT will be better. In practice, the noise is superimposed onto the signal. However, in fine scales, the wavelet coefficients are dominated by noise except some sharp edges, and the effect of signal can be ignored. The plot corresponding to the UDPT using Phaselet transform is given below for block and Heavisine signals.

3.4 SURE Method

The above threshold methods tend to use a high threshold level, and in many cases it oversmooths the noisy signal. Better performance, in terms of the mean squared error (MSE), was obtained with small thresholds. Donoho and Johnstone showed that the Stein's Unbiased Risk Estimator (SURE) could be used as the unbiased estimate of the MSE for the soft thresholding scheme [4]. Johnstone and Silverman later generalized this idea to the case of colored noise, and showed that the SURE method can be also used in the presence of correlated noise.

The SURE value for a specific threshold T and input signal x using the soft thresholding function is given by

$$U(x,T) = \sigma^2 N + \sum_{i=1}^{N}\left\{\min(x_i^2, T^2) - 2\sigma^2 I(|x_i| \leq T)\right\} \quad (11)$$

σ^2 - Noise variance; *I*-Indicator function (I (.)=1 if $|x_i| \leq T$ and I (.) =0 if $|x_i| > T$).

The decision on the choice of threshold is based on comparing $s_d^2 = N^{-1}\sum_{i=1}^{N} x_i^2 - \sigma^2$ (12)

to a threshold

$$T_d = \sigma(\log_2 N)^{1.5} / \sqrt{N} \quad (13)$$

The threshold T used in the SURE method is computed as

$$T = \begin{cases} \sigma\sqrt{(2\log N)}, & s_d^2 \leq T_d \\ T_{SURE}, & s_d^2 > T_d \end{cases} \quad (14)$$

The plot for denoising of signals by SURE method using Phaselet Transform is given below for block & Heavisine.

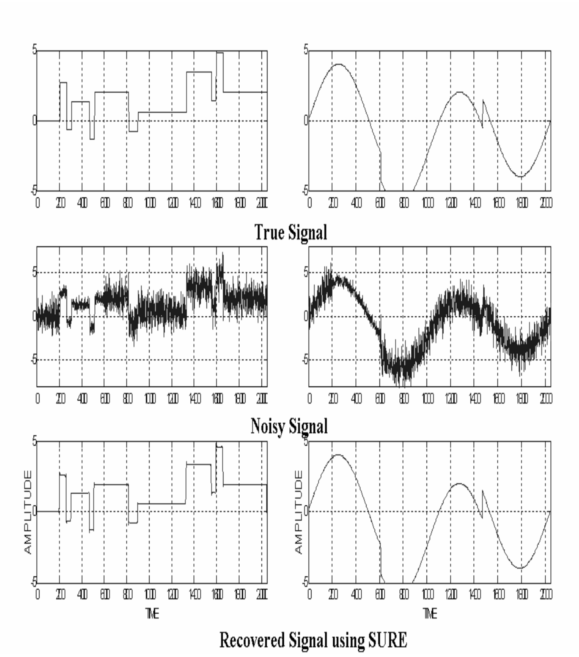

Fig.5 a) Blocks b) Heavisine

4. Conclusion

Using the above de-noising schemes, we can easily determine the noise-shrinkage threshold and reduce the PT of the noise-corrupted. It clearly indicates that there is no disturbance-taking place during the observation period. Therefore, the possibility of false alarm in the PQ monitoring system can be greatly lowered.

The simulation was done using MATLAB 7. Compared with the SSNF technique, threshold-based methods perform better and need less computation. However, the SSNF technique can analyze edges well and can be easily extended to edge detection, image enhancement, and other applications. Simulation results also show that the new method performs better for typical signals. Comparing the SSNF technique with the threshold-based method, the latter performs more satisfactorily and needs less computation, whereas the former can analyze edges satisfactorily and can be extended to edge detection, image enhancement, and other applications. Using the PT approach, the following tabulation was done which gives the SNR for different algorithms which where dealt above. From the table it can be inferred that SURE algorithm provides optimal denoising independent of the input signal.

S.No.	Algorithm	SNR (dB)	
		Blocks	Heavisine
1.	**SSNF**	13.5298	26.3104
2.	**OPT**	8.2602	18.5781
3.	**UDPT**	13.3935	26.3092
4.	**SURE**	12.0914	12.2061

Table 1:SNR Value for different algorithms

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