A Modified Approach for Denoising of Power Line Signals Using Stein's Unbiased Risk Estimator Incorporated with Phaselet Transform

N. P. Subramaniam, M. S. Sudhakar, and K. Bhoopathy Bagan

***Abstract*—Power line signal are normally subjected to disturbance and noise which degrade the overall performance of power quality monitoring system. This paper proposes a modified approach for denoising by combining an algorithm known as Stein's Unbiased Risk Estimator (SURE) algorithm incorporated with phaselet transform (PT). This algorithm is chosen particularly, as it not only performs denoising but also tends to optimally smooth the noisy signal. Since the algorithm is incorporated with phaselet, this leads to increase the coefficients obtained. Hence this method is found to be effective for application for denoising of power line signals. The different types of power quality signals simulated using the proposed method is found to be efficient and provide better results with increased Signal-to-Noise ratio (SNR) when compared with the results obtained by applying wavelet transform (WT).**

***Index Terms*—Denoising, phaselet transform, power quality, SURE algorithm, wavelet transform.**

I. Introduction

POWER quality (PQ) issues have captured considerable attention from utility companies and their customers in recent years, mainly proliferation of sensitive electronic equipment. 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, ecommerce, chemical, automobile and paper manufacturing industries. In particular, as the spectrum of the noise caused due to operation, inference or sampling coincides with that of the transient signals.

The impact of this noise cannot be eliminated by using conventional filters (band pass, FIR and etc,.) without affecting its performance. To overcome this difficulty the disturbance signals can be captured out of the background noise in a low SNR environment and the quality of the performance, can be evolved as if we were processing "pure" signals. The most common limitation of the recursive digital filters, when compared to the non-recursive filter, is incapability of having a strictly linear phase characteristic which could only approximate a constant group delay. In analog filters the choice of the maximally flat criterion leads to the use of the Bessel polynomials. Yet digital approximations of the continuous filter functions are inadequate to yield the true maximally flat delay approximation of the recursive filters. Owing to stability constraints of the filter, the recursive filter may not achieve a strictly flat group delay, but in applications where the high degree of the non-recursive filter is unacceptable, which leads to approximate a linear phase by a recursive transfer function [1].

To improve the effectiveness of the PQ monitoring system, many researchers [2]-[9] have proposed the use of the WT approach for denoising the power line signals. But due to the lack of shift invariance and diffusing of energy into neighboring scales makes the existing methods to be inefficient for denoising. Hence there is a need for a transform to overcome the above said difficulties, which is shift invariant and provides more coefficients and this is provided by PT [10].

In this paper a modified approach has been proposed by combining SURE algorithm incorporated with PT. The PT is a mathematical method of decomposing the signal in the time domain into several scales at different levels of resolution (time-scale domain) through dilations and translations. The phaselet coefficients at the several scales reveal the time localizing information about the variation of the signal from high to low frequency bands. Accordingly, observing scales of the PT can help to exactly capture the power line signals from the noise in the PQ monitoring system.

The paper is organized as follows: Phaselet transform and its application to denoising is described in detail in Section II. The application of SURE algorithm for denoising is explained briefly in Section III and the analysis and performance evaluation of the proposed method is carried out in Section IV. Finally Section V gives the conclusion of the proposed algorithm and the results are described by means of Signal-to-Noise Ratio Enhanced (SNRE).

II. Phaselet Transform

Kingsbury [10] proposed the PT that includes the popular dual tree complex WT. The main idea in this is to use a finite set of wavelets that are related to each other in a special way to achieve approximate shift-redundancy called phaselet. If the numbers of coefficients are more then a better approximation can be achieved. A sufficient condition on the associated scaling filter is that they are fractional shifts of each other.

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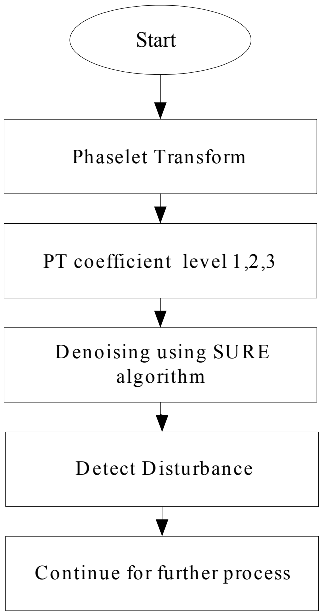


Fig. 1. The structure of denoising system for PQ monitoring system.

Fourier transform (FT) of n – redundant WT having fixed magnitude and fixed phases that are related to each other in a redundant way and hence the resultant transform would be approximately shift invariant. Let us first examine the shift invariance fact by considering for FT. For a random shift τ there is a change $-\omega\tau$ to the phase in the FT. If random shifts are uniform then the corresponding phase shift at each frequency ω is also uniformly distributed in $[-\pi, \pi]$. Depending on this phase the Fourier spectrum at a frequency ω is or is not reflected on the coefficients. The fact that WT preserves energy implies that, when a function is translated by τ, the energy at a particular scale diffuses into neighboring scales. While nothing can be done about it with one WT, it is plausible that with a redundant WT, such wavelets can work together to cancel out the effects of energy leakage of individual WT's across scales. But such function should have a stable profile under translation. This idea leads us to what we call a PT [11].

A set of functions is called a strict phaselet family if their FTs are of the form

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

for $i = 1$; where ω is Frequency, and the scale l is given by $0 \le l < n-1$, where ψ_1 is Phaselet function, generates a tight frame for $L^2(R)$, and

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

where $\theta^l(\omega)$ is Phase shift.

Furthermore, if the vectors are $\{\varphi^l \in R^2\}_{l=0}^{n-1}$ associated with $\{\tau^l\}_{l=0}^{n-1}$ it generates a tight frame for R^2, then the phaselet family is said to be canonical. The number of phaselet n is called the redundancy of the phaselet family. Thus for analysis we take into account a three redundant canonical phaselet family with two vanishing moments. The application of PT thus tends to increase the number of coefficients due to the redundancy introduced into the transform as compared to the conventional WT output. Hence the PT is applied for denoising of power disturbance signals.

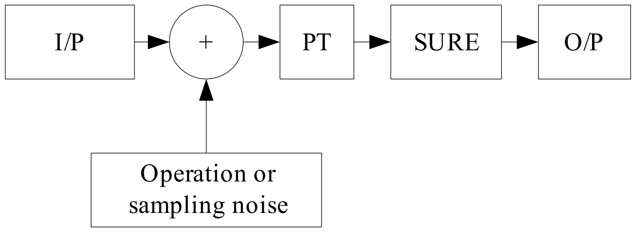


Fig. 2. Addition of noise (due to sampling) to the original signal.

III. SURE Algorithm for Proposed Denoising Scheme

Depicted in Fig. 1 is the structure of the proposed PQ denoising system. The system initiates the collection of data on the disturbance signals in the Digital Fault Recorder (DFR) for the further analysis of PQ events. The system is included the modules of the signal sampling, the Phaselet, the denoising scheme, and the disturbance detector. The analog input signals which (voltage and current waveforms) under observation are received and transformed into digital forms at a given sampling rate. Based on the sample digital data, the PT module is used as band-pass filters to observe in depth variation of the input signals which are out of distinct frequency bands. Fig. 2 shows the block diagram of addition of noise due to operation, inference or sampling coincides with that of the transient signals to the input signal. This noisy signal is used for the testing of the proposed algorithm.

The universal thresholding methods tend to use a high threshold level, and in many case it smoothens the disturbed noisy signal. Better performance, in terms of the mean squared error (MSE), was obtained with small thresholds. Donoho and Johnstone [12] showed that the Stein's Unbiased Risk Estimator (SURE) could be used as the unbiased estimate of the MSE for the soft thresholding scheme [13]. 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 algorithm is obtained after further refinement of the universal thresholding schemes given by Donoho [13]. The algorithm given by Donoho does perform denoising but in many cases it smoothen the signal.

The modified SURE value for a specific threshold T and input signal x using the soft thresholding function is given in (3)

$$U(x,T) = \sigma^2 N + \sum_{i=1}^{N} \left\{ \min(x_i^2, T^2) - 2\sigma^2 I(|x_i| \le T) \right\} \quad (3)$$

σ^2 is the noise variance; I is Indicator function ($I(.) = 1$ if $|x_i| \le T$ and $I(.) = 0$ if $|x_i| > T$).

The SURE threshold is obtained as

$$T = \arg\min_{0 \le T \le \hat{\sigma}\sqrt{2\log N}} \hat{U}(x,T) \quad (4)$$

for level dependent thresholding, the noise variance $\hat{\sigma}_j^2$ for level j can be obtained using the median absolute deviation (MAD)

$$\hat{\sigma}_j = \frac{MAD(z_{j,k})}{0.6745} \quad (5)$$

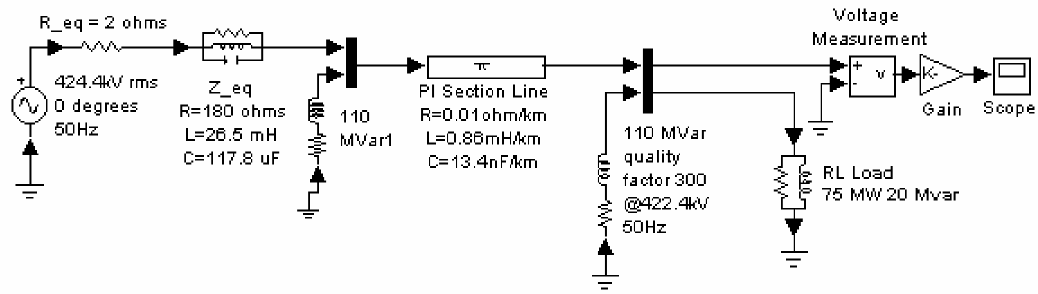
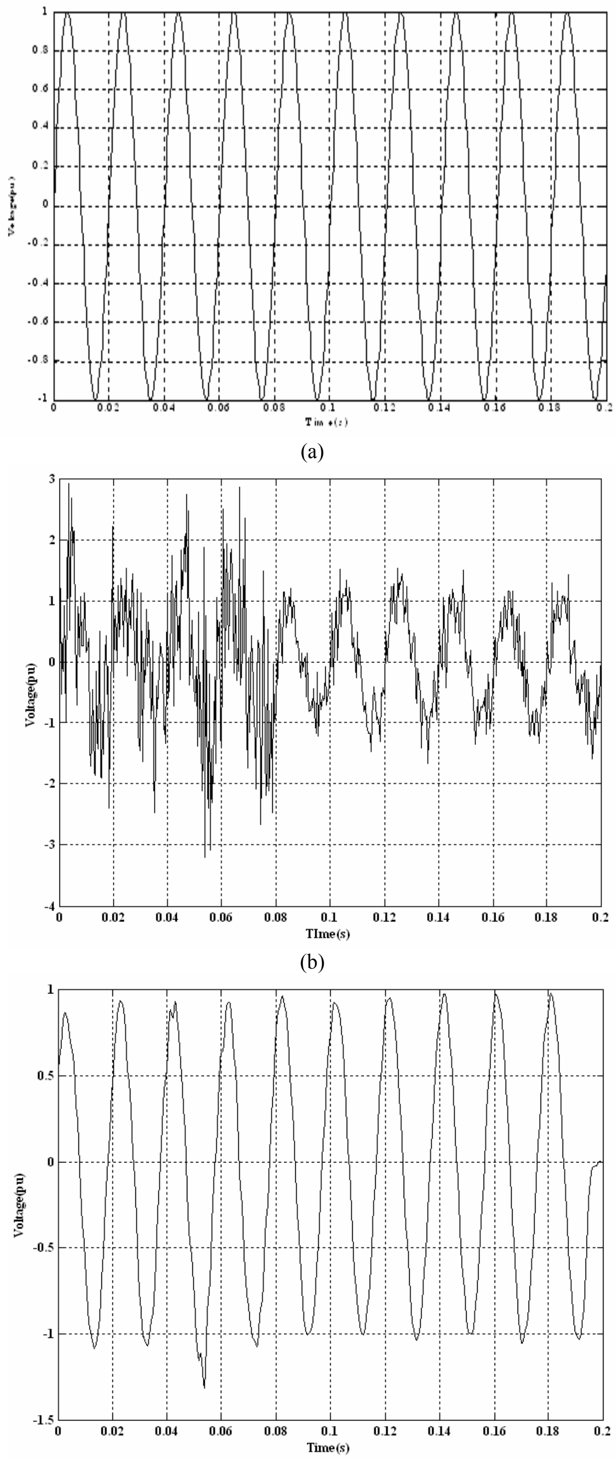


Fig. 3. The circuit for simulating various disturbances in MATLAB SIMULINK.



(a)

(b)

(c)

Fig. 4. (a) Pure sinusoidal signal, (b) Noisy signal, and (c) Sinusoidal signal after denoising.

where 0.6745 is a normalization factor. The operator MAD picks out the median of absolute values of all the wavelet coefficients $z_{j,k}$ at resolution level j. Thus the heuristic SURE method, selects either the universal threshold or the SURE threshold according to a test of significance presence of the signal to nullify the noise.

The decision on the choice of threshold (T_d) is based on comparing

$$s_d^2 = N^{-1}\sum_{i=1}^{N} x_i^2 - \sigma^2 \tag{6}$$

to a threshold

$$T_d = \sigma(\log_2 N)^{2.5} / \sqrt{N} \tag{7}$$

The threshold T used in the SURE method is computed as

$$T = \begin{cases} \sigma\sqrt{(2\log N)}, s_d^2 \le T_d \\ T_{SURE}, s_d^2 > T_d \end{cases} \tag{8}$$

It was shown that when noise dominates the observed data, this universal threshold method performs better, and when the underlying signal dominates the observed data, the proposed method performs better.

IV. SIMULATION RESULTS

The proposed denoising scheme has been developed and tested using the simulated and actual field data for various disturbances with noise. This method was simulated using MATLAB® tool.

The simulated testing cases using the MATLAB® Power System Blockset include the disturbances of voltage sag, voltage swell, and transients with diverse levels of noise. The diagram of the circuit for the simulations in MATLAB® SIMULINK is given in Fig. 3. The sampling rate of the input signals was set at 4001 points/s with 256 sampling points for each cycle in average. The base of 424.4 kV is used for the voltages (in per unit) given in the testing results (Figs. 4-7). On the other hand, data for the actual field tests (described in sub-section IV-E) were obtained from 230 kV and 110 kV-level power systems, respectively, for the two cases of voltage sag.

A. Noise-Corrupted Normal Signal

To test the effectiveness of the denoising scheme of the PT, the first testing case is a normal signal without disturbance. The signal received is a pure sinusoid but corrupted with random noise. Fig. 4(a) exhibits the simulated input sinusoidal signal without noise. The input signal with noise is depicted in Fig. 4(b). Although variations in the amplitude are small, the nonzero phaselet would give false

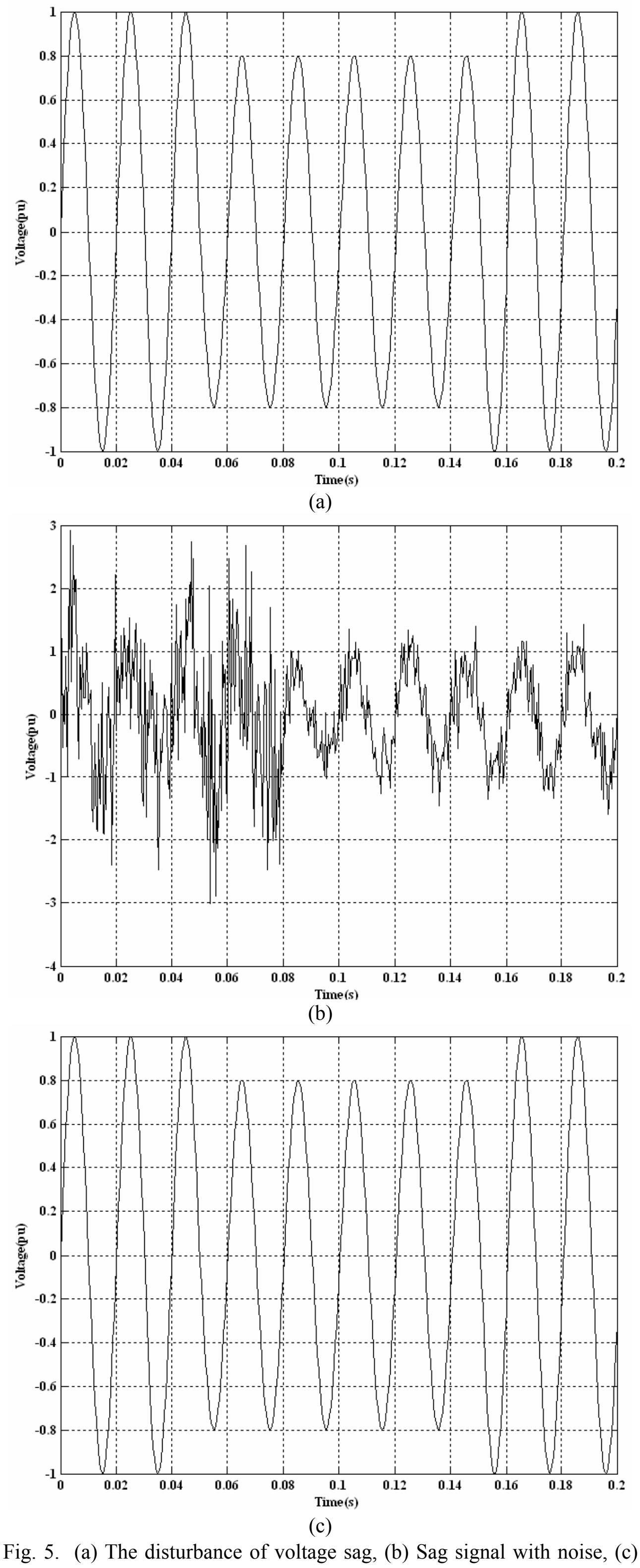


Fig. 5. (a) The disturbance of voltage sag, (b) Sag signal with noise, (c) Sag signal after denoising.

alarm for the detection of disturbances. Also, the threshold of shaving away the noise is often hard to set automatically, since the corresponding phaselet to the disturbances may be relatively small and the disturbances happen to occur near the zero-crossing points of the signal can not be diagnosed.

Using the denoising scheme described above, we can easily determine the noise shrinkage threshold and reduce the phaselet of the noise corrupted signal to those shown in Fig. 4(c). This figure clearly indicates that there is no disturbance taking place during the observation period. Therefore, the possibility of false alarm in the PQ system can be greatly lowered.

B. Voltage Sag

A PQ system is often obligated to precisely capture the occurrence of the voltage sag and swell disturbances in order to find possible solutions and to remedy for problem. Fig. 5(a) is a simulated 20% voltage sag signal caused by switching the load in Fig. 3 to a heavier one for five cycle duration and then switching it back. When there is no noise on the signal, the first scale phaselet of the signal can obviously indicate the start and end time of the sag disturbance.

However, as the signal monitored is contaminated by noise, it is difficult to detect the disturbance from the phaselet of the signal. We might observe the two main spikes of the phaselet which stand for the occurrence of disturbances. However, it still remains difficult even if the computer detect it, when the phaselet magnitudes of the disturbance and the noise are variable. Through the denoising scheme proposed in this paper, the Phaselet in Fig. 5(b) are reduced into those shown in Fig. 5(c). After denoising, the Phaselet in Fig. 5(c) now depicts as clearly shown in Fig. 5(a) where no noising effects are imposed.

C. Momentary Interruptions

A momentary interruption can be seen as a momentary loss of voltage on a power system. Such disturbances describe a voltage drop of 90 to 100% of the rated system lasting for 0.5 cycles to 1 min. Fig. 6(a) shows the contours for a momentary interruption of a power lasting for 5 cycles. Fig. 6(b) gives the values when noise is added to the input signal. The noise somewhat confuse the alarm of the impulse event. The result of the denoising scheme to clean up the noise is displayed in Fig. 6(c). The phaselet again provide concise alarm of the occurrence of the impulses.

D. Noise Tolerance Testing

To test the ability of the PQ system in tolerating the noise on the input signal, different levels of noise with the SNR values ranging from 50 to 25 dB were used. The value of the SNR is defined as

$$SNR = 10\log(P_S / P_N) \qquad (9)$$

where P_s is the variance (power) of the signal, and P_N is that of the noise. The data for the four types of disturbances (including the interruption events besides those mentioned above) and different SNR in dB values were simulated. For each disturbance, total 100 cases were created and the results are given in Table I. The reconstruction of the denoising signals for the PQ system were compared with the results of existing method.

E. Actual Field Testing

To validate the performance of the denoising scheme more realistically, two sets of actual field data for cases of voltage sag and swell were derived from 230 kV-level (with PT ratio 400 : 1) and 110 kV-level power systems of Ennore Thermal Power Station, Tamilnadu. Shown in Fig. 7(a) is the event with sudden sag of voltage waveform

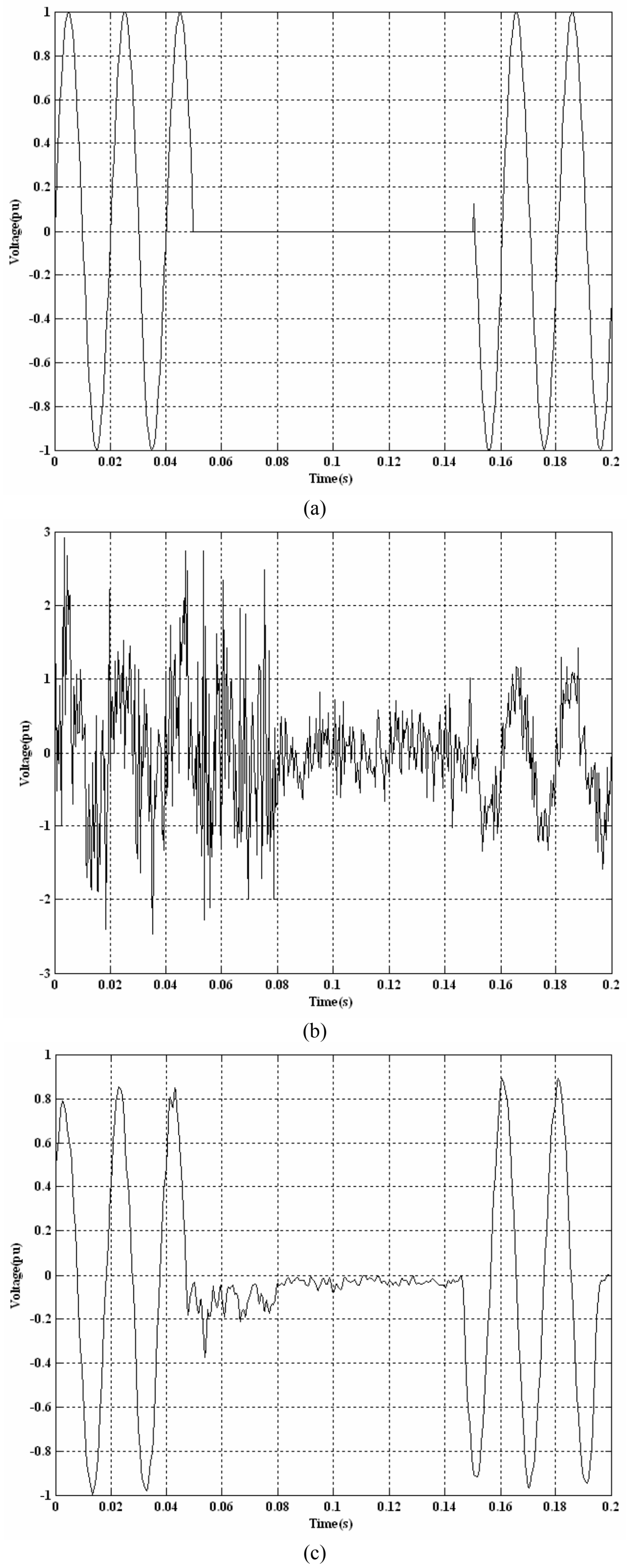


Fig. 6. (a) The disturbance of momentary interruptions, (b) Momentary interruptions with noise, and (c) Momentary interruptions after denoising.

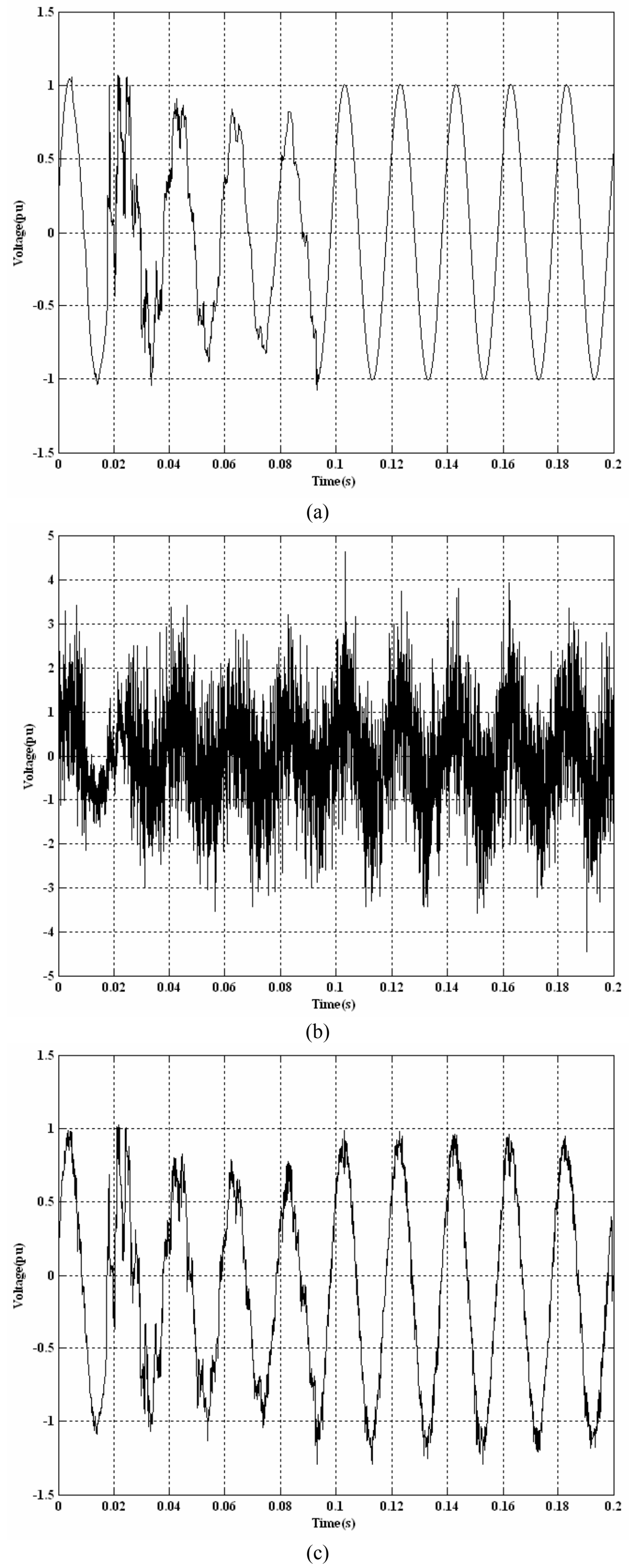


Fig. 7. (a) The waveform of voltage sag (Real data), (b) Sag signal with noise, and (c) Sag signal after denoising.

TABLE I
RECONSTRUCTION RATE (%) OF DIFFERENT SIGNALS AFTER DENOISING

SNR (dB)	Sine		Sag (simulated)		Sag (Real data 1)		Sag (Real data 2)		Swell		Momentary Transients	
	PT	WT	PT	WT	PT	WT	PT	WT	PT	WT	PT	WT
50	100	100	100	100	100	100	100	100	100	99	100	100
45	97	85	97	82	95	80	96	80	97	80	96	83
40	90	72	86	69	83	65	83	64	86	66	89	71
35	76	63	74	63	73	58	72	56	74	63	76	63
30	65	50	65	45	62	39	65	40	66	44	65	50
25	54	35	50	30	50	28	49	30	50	30	52	35

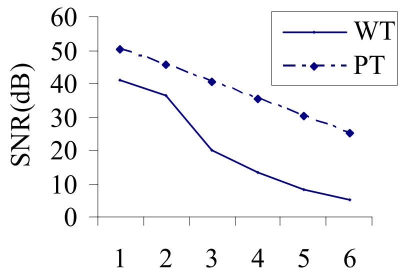


Fig. 8. Comparison of SNR for PT and WT in different samples.

at about 60ms due to a heavy load switched on. The signal was recorded with noise added is shown in Fig. 7(b). It is noticed that the noise on the signal indeed makes the PQ monitoring system lose its performance. This noise is introduced in the process of data acquisition and communications in fact are not easy to be characterized accurately. Basically, the frequency content of the noise is often higher than the ordinary power harmonics. However, one cannot get rid of the noise from the signal through a low pass filter, as they would also remove high frequency transient signals along with noise. Assuming the noise is of white Gaussian distribution, the denoising scheme is able to set a threshold adaptively for each scale of the phaselet. This provide better denoising scheme and shown in Fig. 7(c) which pinpoints clearly the occurring time of the voltage sag by a single impulse of phaselet.

Thus it can be inferred from the above result that the SURE algorithm performs well for denoising and provides optimal smoothing thereby retaining the original signal with utmost preciseness. The performance of PT is evaluated by generating the disturbed signal with different SNR and reconstructing the signal after denoising. The percentages of reconstruction rate for different type of signals are shown in Table I. This results show that PT was found to be better when compared to WT for all ranges of SNR. Fig.8 shows the comparison of SNR for PT and WT for one type of disturbed at different samples.

V. Conclusions

As a conclusion, it can be said that a new and simple algorithm has been proposed for denoising the power line signals using PT. By applying the PT the numbers of coefficients were increased due to the introduction of redundancy into the transform. The key property of shift invariant and reduction in the diffusing of energy in various scales makes the above method efficient with increase in the SNR. When noise is present, the malfunctioning of alarming is prevented with help of proposed method. We have demonstrated the efficiency of PT methods by denoising the real time signals. Thereby minimizing the noise and increase the SNR while preserving the reconstructed signals, in such way that it is virtually matched with the original signal. The proposed algorithm is robust and generalized for other type of signals.

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