Time-frequency Filtering of Gaussian and Impulse Noise for Spread Spectrum Power Line Communication

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Abstract: The affluence of impulse noise is one of the challenging problems of the power line communication (PLC) as a communication channel. However, current methods for impulse noise reduction are either not effective or requiring heavy computing for detecting impulse noise accurately. This paper presents a time-frequency filter design method for impulse and Gaussian noise mitigation by a reliable noise detector in the wavelet domain with local variance analysis. The filtering is applied only to the detected noisy samples with others unchanged in an effort to reduce the noise level by adapting its operation in accordance with variance characteristics. The received corrupted signal from spread spectrum system is decomposed into time-frequency domain by fast implementation of lifting wavelet transform for real-time filtering of mixed Gaussian and impulse noise. Experimental results demonstrate that the proposed method can significantly reduce impulse noise and improve bit error rate (BER) without introducing distortion, leading to better quality of service.

1 INTRODUCTION

Power line communication (PLC) offers many advantages over other wire line and wireless communication technology that makes it efficient and economic to use for many years. The main driving force lies in that communication over power lines can provide good business opportunities for a variety of different areas including electrical power engineering, communication networks as well as building automation, because the networks are almost universal in coverage and are easily accessed by wall plugs (Guo, 2005). However, unlike the other wired communication mediums such as the unshielded twisted pair (UTP) and coaxial cables, low voltage (LV) power lines present an extremely harsh environment for channel parameters namely, noise, impedance mismatch and attenuation are found to be highly unpredictable and variables with time, frequency and location (Hossain et al., 2008). Even though power lines are an attractive solution for data transmission, a reliable communication is a great challenge due to the nature of the medium (Pighi and Raheli, 2007).

The power line is often considered an unpredictable environment due to the time-variant characteristics of the noise and the attenuation, which limits the performance that can be achieved (Biglieri, 2003). The noise level and the attenuation depend partly on the set of connected loads, which varies in time (Barmada et al., 2006). The noise power on the power line is a sum of many different disturbances. Noise on the power line, is influenced by a large number of different noise sources with different characteristics. There are broadband disturbances such as universal motors, and narrowband disturbances such as radio frequency signals. Generally speaking, the dominant channel disturbances occurring in power line channels are colored background noise, narrowband interference and impulse noise (Gotz et al., 2004); (Degardin et al., 2002). Background noise is caused by assembling of multiple sources of noise with low power, and can be modeled as a white noise process (Mlynek et al., 2010). Narrowband interference (NBI) could originate from frequency/phase modulated signals from broadcasting stations. Impulse noise can be classified into three classes (Tiru and Boruah, 2010): (i) periodic impulse noise

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asynchronous with the AC mains; (ii) periodic impulse noise synchronous with the AC mains; (iii) asynchronous impulse noise.

Besides the background noise and the narrowband noise which can be effectively reduced by wavelet notch filter (Luo, 2010), impulsive noise adversely affects the quality of service (Degardin, 2002). Impulse noise (IN) is a serious problem for reliable communication over power lines (Lampe, 2011). Its affluence is one of the challenging problems of the power line communication (PLC) as a communication channel. Impulsive noise is one of the most difficult transmission impairments to suppress and has not been well characterized and understood. It consists of random occurrences of energy spikes with random amplitude and spectral content, and affects data transmission by causing bit or burst errors. As the ability to reject high levels of interfering signals is one of the primary benefits of spread spectrum communications, spread spectrum modulation for resistance to jamming and multipath is often used (Zhou et al., 2002). One of the advantages using direct sequence spread spectrum (DSSS) systems is an inherent immunity to interferences, due to the processing gain (Proakis, 2001), i.e. bandwidth expansion factor. However, this immunity is only effective up to certain interference power, making it necessary to apply additional techniques to suppress the effect of strong impulse noise. Impulse noise has already been proved as the most influential noise that degrades bit error rate properties because impulse components of voltage and current waveforms occur in wide frequency bands widely due to switching of semiconductor devices in home appliances. Among all the types of noise, the asynchronous impulse one is probably the most difficult to deal with and leads to heavy detection and computing time (Guillet et al., 2009). Impulse noise is difficult to remove by conventional linear filters and wavelet denoising method (Kuzume et al., 2000). Noise reduction methods using wavelet transform take full advantage of the localization both in time and frequency, and the wavelet shrinkage technique is used to reduce Gaussian noise (Donoho and Johnstone, 1994). However, the nonlinear wavelet transform thresholding method is not effective for impulse noise reduction or requiring heavy computing for detecting impulse noise accurately. One of the main properties of the classical filters is that all input samples are unconditionally affected by the filtering process. In the presence of impulse noise, this approach is not optimal in contrast to continuous noise distributions, only certain samples of the original signal are corrupted and others remain unchanged. Clipping is a popular technique for impulsive noise reduction (Al-Mawali and Hussain, 2009; Kim et al., 2011). At the receiver the occurrence of an impulse is determined with a set threshold and is corrected by replacing it by clipping operation on the amplitude of the input signal samples. The problem, however, is that the definition of impulse length and the detection of an impulse altogether is threshold dependent. And the clipping method with nulling strategy may introduce distortion or cause detrimental effects to the signal.

Due to the high unpredictability of the impulsive noise, a good knowledge and characterization of such noises is essential for their mitigation (Khngosstar et al., 2011). To effectively detect and suppress impulse noise with less signal distortion, this paper explores the impulse noise characteristics and presents a time-frequency filter design method for impulse and Gaussian noise mitigation by reliable noise detection in the wavelet domain.

2 TIME-FREQUENCY ANALYSIS OF NOISE

Impulse noise consists of energy spikes with random amplitudes and spectra. Because of its non-stationary unpredictable nature, impulse noise does not lend itself easily to a statistical description. A mathematical model of noise in closed form for power line communication can be expressed as a probability density function (PDF) (Katayama et al., 2006):

$$P(n(t)) = \frac{1}{\sqrt{2\pi\sigma^2(t)}}\exp(-\frac{n^2(t)}{2\sigma^2(t)}) \tag{1}$$

where $n(t)$ denotes the noise, $\sigma^2(t)$ is the instantaneous variance of the noise. In particular, the PDF of impulse noise can be expressed as a sum of Gaussian functions with different variances. The noise waveform generated with this model shows good agreement with that of actually measured noise (Katayama et al., 2006). It is obvious that the noise power is time function as well as frequency. Wavelets introduce new classes of basis functions for time-frequency signal analysis and have properties particularly suited to the transient (impulse like) components (Barmada et al., 2011). The basic premise of wavelet transformations is that for any given signal it is possible to decompose this signal into many functions through translations and dilations of a single function called a mother wavelet. Wavelet decomposition can be used to detect and remove impulsive noises with transient nature. To effectively suppress impulse noise, we use two features of spread spectrum communication to discriminate signal from impulse noise: one is the smooth envelope of spread signal's spectrum (An example of smooth spectrum of spread spectrum signal without added noise is shown in Figure 1) and the other is the nature of transient noise (An example of spread spectrum signal with mixed Gaussian and impulse noise in the time doamin is shown in Figure 2 and Figure 3 shows the details of the impulse noise).

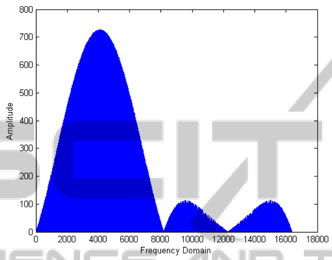

Figure 1: An example of smooth spectrum of spread spectrum signal without added noise.

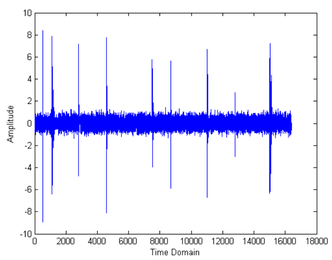

Figure 2: An example of spread spectrum signal with mixed Gaussian and impulse noise in the time doamin.

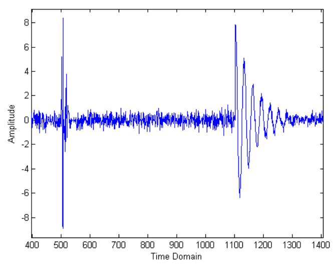

Figure 3: Details of the impulse noise.

Wavelet analysis is effectively a mathematical microscope, which allows the user to zoom on features of interest at different scales and locations. However, the need for improvement of wavelets comes from a shortcoming that is inherent because of its construction. Second generation wavelets (Sweldens, 1998), open a new direction to construct wavelets, and are more general in the sense that all the classical wavelets can be generated by the lifting scheme. The lifting scheme makes optimal use of similarities between the high and low pass filters so as to achieve a faster implementation of WT.

Classical implementation of WT uses two band filter bank (FB) with recursion on its low pass (LP). Equivalent polyphase representation is depicted by polyphase matrix $\tilde{P}(z)$, which is assembled from even and odd filter components. Output of the FB is:

$$\begin{bmatrix} LP \\ HP \end{bmatrix} = \tilde{P}(z)\begin{bmatrix} y_{even} \\ z^{-1}y_{odd} \end{bmatrix} \tag{2}$$

where HP denotes high pass and y_{even} is the even part of the signal, and y_{odd} is the odd part.

$$\tilde{P}(z) = \begin{bmatrix} \tilde{h}_e(z) & \tilde{h}_o(z) \\ \tilde{g}_e(z) & \tilde{g}_o(z) \end{bmatrix} \tag{3}$$

For any filter pair (h,g) with $\det[P(z)] = 1$, always exist factorisation of $P(z)$ (Daubechies and Sweldens, 1998):

$$P(z) = \begin{bmatrix} K & 0 \\ 0 & \frac{1}{K} \end{bmatrix} \prod_{i=m}^{1} \left\{ \begin{bmatrix} 1 & s_i(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_i(z) & 1 \end{bmatrix} \right\} \tag{4}$$

Equation (7) allows ladder realization of $\tilde{P}(z)$ by reversible lifting steps followed with normalization by factor K as shown in Figure 4.

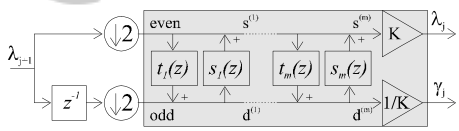

Figure 4: Ladder structure of lifting steps.

Signal is partitioned into even and odd components that are then mutually predicted by t_i (to zero signal in HP part) and updated by s_i (to retain in LP part signal moments). After normalization the algorithm is recursively applied to LP part.

In this study, 9/7 filter pair for fast computation is used by factoring wavelet transform into lifting steps. This filter pair is smooth and relatively short. The analysis low pass filter has 9 coefficients, while the synthesis high pass filter has 7 coefficients. This is particularly suited to time-frequency analysis of spread spectrum signal with strong noise applied to power line. The lifting wavelet transform can be implemented using the following lifting coefficients:

$$\begin{gathered} \alpha_1^{(1)} = -1.586134342\ ; \beta_1^{(1)} = -0.0529801185\,4\ ; \\ \alpha_1^{(2)} = 0.8829110762\ ; \beta_1^{(2)} = 0.4425068522\ ; \\ K = 1.14960439\,8\,. \end{gathered} \tag{5}$$

The lifting wavelet transform and the inverse transform by lifting coefficients in floating-point format is at the core of time-frequency analysis and consumes the bulk of the processing time. This is because performing signal decomposition requires many multiplication operations, which increase the computational complexity. To speed up the computation, lifting coefficients can be quantized to 32-bit word-length, allowing fixed-point arithmetic to be implemented so that all multiplications can be replaced by bit shifts and additions to reduce computational load.

3 NOISE DETECTION AND FILTERING

Consider a baseband digital DSSS (direct sequence spread spectrum) communications system, the received signal $y(t)$ can be modelled as

$$y(t) = s(t) + n_w(t) + n_{im}(t) \quad (6)$$

where

$$s(t) = Ad(t)c(t)\cos(2\pi f_c t)$$

and $n_w(t)$ is background noise, $n_{im}(t)$ is impulse noise, $s(t)$ is binary phase shift keying (BPSK) direct sequence spread spectrum signal, $d(t)$ is a binary sequence of data symbols taking on values ± 1, $c(t)$ is the spreading sequence (PN code) taking on values ± 1, f_c is the carrier frequency of the transmitted signal.

The time-frequency localization provided by wavelet promises a possibility for better discrimination between the noise and the real data. In the case of direct observations of the object y, the wavelet transform of the data results in coefficients $\{d_\lambda\}$ of the form using inner product

$$d_\lambda = < y, \Psi > + \sigma z_\lambda \quad (7)$$

where d_λ represents wavelet coefficients, Ψ is wavelet function, y denotes object, $\{z_\lambda\}$ represents a noise process. Specifically, by taking the wavelet transform of the data, we obtain a representation which contains the main structure of the signal in a relatively few large coefficients, and the noise in the remaining small coefficients. This is because in most cases, noise can generally be represented as a normally distributed (Gaussian), zero-mean random process. Thus, it is required to calculate a threshold value to identify the insignificant coefficients, which may be considered as noise (noise coefficients). This thresholding is adaptively subband dependent and is based on local variance analysis. The formula for the threshold on a given subband *j* is

$$\lambda_j = \frac{\hat{\sigma}^2}{\hat{\sigma}_X} \quad (8)$$

where $\hat{\sigma}^2$ is the estimated noise variance, and $\hat{\sigma}_X{}^2$ is the estimated signal variance on the subband considered. The noise variance is estimated as the median absolute deviation of the coefficients on level 1 (highest frequency subband):

$$\hat{\sigma} = \frac{Median(|W_i|)}{0.6745}, \text{ where } W_{i \in subband\ 1} \quad (9)$$

The estimate of the signal standard deviation is

$$\hat{\sigma}_X = \sqrt{\max(\hat{\sigma}_W{}^2 - \hat{\sigma}^2, 0)}, \text{ where } \hat{\sigma}_W{}^2 = \frac{1}{n^2}\sum_{i=1}^{n} W_i^2 \quad (10)$$

$\hat{\sigma}_W{}^2$ is an estimate of the variance of the observations, with *n* being the number of the wavelet coefficients on the subband under consideration.

For Gaussian noise filtering, we define

$$T_j = a\lambda_j \quad (11)$$

where *a* ($0 \le a \le 1$) is a parameter that can be used to moderate the shresholding to optimize the trade-off between hard and soft thrsholding of wavelet shrinkage technique for Gaussian noise reduction as

$$S(d_\lambda) = sign(d_\lambda)(|d_\lambda| - T_j), \text{ if } |d_\lambda| > \lambda_j$$
$$= 0, \text{ otherwise} \quad (12)$$

and *a* is set at subband *j* adaptively to $\hat{\sigma}^2$ as

$$a_j = \frac{\hat{\sigma}^2}{(\hat{\sigma}^2 + \hat{\sigma}_X{}^2)} \quad (13)$$

The wavelet coefficients at each level (subband) are treated separately, so the threshold λ_j depends only on the values of the coefficients at level *j*. Adaptivity in this technique is based on local variance analysis. By utilizing the parameter *a* with local variance analysis, this method improves the soft wavelet shrinkage technique to optimally reconstruct a signal from samples contaminated by Gaussian noise. In this method, small wavelet coefficients are set to zero since they are likely to contain little signal energy, and larger wavelet coefficients are scaled down since they are likely to contain greater signal energy. In such a way, noisy wavelet coefficients are eliminated by comparison to the predetermined threshold.

When studying the effects of impulsive noise on PLC, both background noise and impulsive noise are considered. To reduce impulse noise with less signal distortion, it is required to detect impulse events and identify correctly their temporal boundaries in a stream of noise signal samples that also contains nonimpulsive background noise. As impulse noise can be expressed as a sum of Gaussian functions with different variances, it can be detected by measure the changing variance through a sliding window with subsequent overlapping sections of the signal. In each window with *N* samples (wavelet coefficients) on the subband, the variance is

$$\hat{\sigma}_w^2 = \frac{1}{N^2}\sum_{i=1}^{N} W_i^2 \tag{14}$$

If the variance of the windowed wavelet coefficients is higher than a threshold, the window is marked as containing an impulse thus the location of impulse noise is detected. The threshold value is determined by calculating the median of variances of windowed samples on each subband. The threshold can be set at median value multiplied by 1.2 to determine the presence of impulse noise in a window as

$$\lambda_v = Median(\hat{\sigma}_W^2)*1.2 \tag{15}$$

Then from equation (6), we obtain the estimated signal $\hat{s}(k)$ by using a filter $h(k)$ as

$$\hat{s}(k) = h(k)y(k) \tag{16}$$

because $y(k) = m_y + (y(k) - m_y)$, where m_y is the mean of $y(k)$, we have

$$\hat{s}(k) = h(k)(m_y + (y(k) - m_y)) \tag{17}$$

If the filtering would not take effects to the mean m_y and we would consider always reducing noise variance, the filter $h(k)$ can be designed:

$$h(k) = \frac{\hat{\sigma}_y^2}{(\hat{\sigma}_y^2 + \hat{\sigma}^2)} \tag{18}$$

where $\hat{\sigma}_y^2$ is the variance of the observations, $\hat{\sigma}^2$ is the noise variance. Thus the impulse noise filtering operation can be performed in the time-frequency domain by the filter on each subband *j*:

$$\hat{s}_j(k) = m_W + (W_k - m_W)\frac{\hat{\sigma}_W^2}{(\hat{\sigma}_W^2 + \hat{\sigma}^2)} \tag{19}$$

where $\hat{s}_j$ is the estimated signal at level *j*, *W* is the received signal, and m_W is the mean of *W*. The filtering is applied only to the noisy windowed samples which accounts for the impulse clustering. The filtering is iterated until the variance of the filtered samples is equal to or lower than λ_v, such that the impulse noise with short term fluctuations is smoothed out. The signal-adaptive filter can always reduce the variance namely the noise level of the detected noisy samples by adapting its operation in accordance with local variance characteristics. By applying “no filtering” to preserve true signals and filtering to remove impulse noise with a robust estimator, impulse is detected and mitigated. The algorithm is straightforward, low in complexity, achieves high filtering performance and requires no previous training.

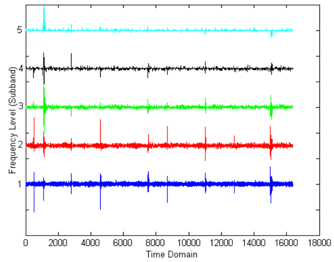

Figure 5: An example of time-frequency decomposition using the original signal shown in Figure 2.

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

Background and impulse noise are among principal impairments in PLC channels. Spread spectrum power line noise detection and suppression is performed by fast time-frequency wavelet decomposition and variance analysis. To evaluate the noise suppression versus bit error rate (BER), a spread spectrum system was set up for power line communication. The system spreading code is a maximal sequence 511 chips PN code clocked at a 1 MHz chip rate. The data spreading signal is mixed with a carrier frequency (centred on 5 MHz) by binary phase shift keying (BPSK) to generate the transmitted spread spectrum signal. Spreading signal is transmitted by power line channel with mixed additive white Gaussian noise (AWGN) with mean zero and impulse noise. Impulse noise is generated for power line channel with different variance, length (decay rate) and spike (amplitude and spectral content). Different impulse noise (periodic or nonperiodic, asynchronous or synchronous with the AC mains) is applied to the channel. BPSK interfering signal from the output of the channel then enters the receiver. At the receiver, modulated signal is demodulated by mixing with 4 MHz to downconvert to IF (intermediate frequency) frequency at 1 MHz. The final detection output is obtained through FFT (fast Fourier transform) based correlation. Noise detection and suppression is performed in the wavelet domain on each subband of decomposed data (8 PN codes with 8 bit symbols for one frame, an example of time-frequency decomposition for 5 subbands is shown in Figure 5 using the original signal shown in Figure 2) and the final results are measured by conducting bit error rates (BER) performance comparison against signal to noise ratio (SNR) at one noise level set. The noise impulses are characterised with high energy levels and the SNR of symbols affected by impulse noise is typically very low. In the process of noise detection and suppression, Gaussian noise is first detected and removed by the proposed improved soft thresholding technique. Impulse noise detection is done by local variance analysis through a sliding window of 16 samples with subsequent overlapping sections of 8 samples. Figure 6 shows the resultant variances by the sliding window using corrupted signal shown in Figure 2 and the corresponding time-frequency decomposition shown in Figure 5. The designed time-frequency filter only applies to the windowed samples marked as impulse, and the corresponding wavelet coefficients are then smoothed out. Figure 7 shows the filtering results by mixed Gaussian and impulse noise suppression in the wavelet domain. Finally inverse wavelet transform is performed to transform the signal back to the time domain for symbol detection. The corresponding bit error rates (BER) are calculated by summing 10000 runs of the demodulated signals (10000 blocks of data) when transmitted over a noisy power line channel producing impulse noise (with different variances) in accordance with different Gaussian noise level. The measurement results are summarized and shown in Figure 8 by illustrating BER measured versus SNR in dB. A comparison is performed by measuring BER of spread spectrum signal with mixed Gaussian and impulse noise, signal after soft thresholding for Gaussian noise reduction, signal after improved soft thresholding for Gaussian noise reduction, and signal after mixed Gaussian and impulse noise detection and suppression respectively. It can be seen that the proposed method of mixed noise suppression significantly reduces impulse noise thus improves BER for better data communication over power lines.

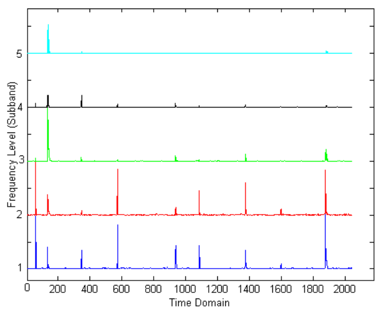

Figure 6: Variance estimation through sliding window in the time-frequency domain.

Experimental results show that the proposed method is able to significantly reduce impulse noise without degrading the quality of the signal or introducing distortion. It is noted that the filtering of both Gaussian and impulse noise is highly computationally efficient by fast implementation of lifting wavelet transform.

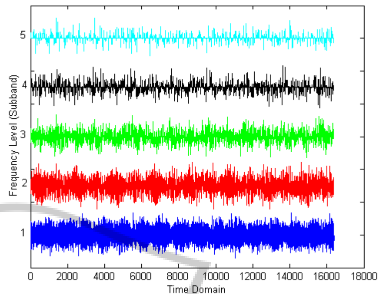

Figure 7: Mixed Gaussian and impulse noise suppression in the wavelet domain.

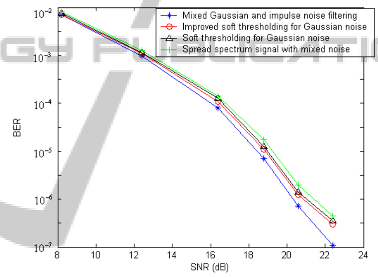

Figure 8: Comparison of BER measured versus SNR.

5 CONCLUSIONS

The proposed method of mixed Gaussian and impulse noise detection and mitigation by local variance analysis in the wavelet domain, applies iterative, selective and adaptive filtering on the corrupted spread spectrum signal over power lines. The filtering is applied only to the detected noisy samples with others unchanged in an effort to reduce the noise level by adapting its operation in accordance with variance characteristics. Experimental results demonstrate that this method removes impulse and Gaussian noise, also simultaneously preserves signal features and improves bit error rate (BER) for better quality of service provided by spread spectrum power line communication. The developed lifting wavelet transform results in a fast implementation of the time-frequency filtering operation, and makes it highly computationally efficient and suitable for real-time applications.

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