A fast converging method for Common Mode Sensor based Impulse Noise Cancellation for Downstream VDSL

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***Abstract*—Impulse noise cancellation using an additional common mode sensor at the customer premises equipment (CPE) receiver is akin to an interference cancellation problem in a SIMO receiver. However, the common mode (CM)-differential mode (DM) cross-correlation for impulse noise signal needs to be estimated during showtime in the presence of a much stronger DM useful data signal. Existing works on this topic rely on the repetitive nature of impulse noise and use a large number of DMT symbols for estimation of the canceler and are therefore not suitable for handling transient noise events. We propose an iterative decision-directed method based on alternating minimization which can provide partial cancellation of the impulse noise using a single DMT symbol (useful for transient noise) and much faster convergence using multiple DMT symbols as compared to existing methods (useful for repetitive impulse noise) and demonstrate its efficacy via simulation.**

I. Introduction

In wireline VDSL/G.Fast systems, impulse noise is generally a high power intermittent noise coupling electromagnetically into the cable binder with the common sources of such noises at the CPE being power line carrier modems and household appliances like washing machine, treadmill etc. Impulse noise can be classified into two types: Repetitive Electrical Impulse Noise (REIN) and non-repetitive or transient Prolonged Electrical Impulse Noise (PEIN) [1]. Impulse noise causes severe degradation in SNR and mitigating the impact of impulsive noise sources via re-transmission [2] or interleaved Reed-Solomon code based forward error correction (FEC) with erasure decoding [3] introduces extra delay and redundancy. Partial or complete impulse noise cancellation can help reduce the redundancy and delay requirements for FEC and in general will improve the overall reliability of the system.

A number of transient impulse noise cancellation methods for single sensor OFDM receivers have been proposed in literature ranging from non-linear processing like blanking/clipping [4] to methods based on the reserved sub-carriers [5][6]. Methods using non-linear processing make assumptions about the noise envelope being much stronger than the signal envelope while methods based on reserved sub-carriers assume that the noise is sparse. By using an additional sensor in the form of the common mode sensor [7][8][9] at the CPE, one can avoid the above strong assumptions on the structure of the noise for its cancellation.

VDSL uses the differential mode for transmission of the useful data signal over the unshielded twisted pair (UTP) due to its robustness to electromagnetically (EM) coupled noise. EM coupled noises like crosstalk and impulse noise couple onto the twisted pair as common mode signals and a fraction of the coupled noise leaks into differential mode due to imbalances in the twisted pair. At the same time, the useful data signal in differential mode also leaks into common mode due to the same imbalance effect. In an ideal twisted pair with no imbalances there will be no leakage between common and differential modes and the common mode rejection ratio will be infinite but in reality the imbalances do exist due to asymmetries in the construction of the twisted pairs and geometry of the cable binder. It has been seen that the CM-DM coupling for the impulse noise and the DM-CM coupling for the data signal can be modelled as an LTI system represented as a finite impulse response (FIR) filter [7][10] and therefore, CM sensor based alien or impulse noise cancellation can be treated as an interference cancellation problem in a single input dual output (SIDO) system.

Noise cancellation can be effected by linearly combining the CM and DM signals provided the optimal CM-DM combining function can be estimated. Since the CM-DM impulse noise cross-correlation is dependent on the noise source, estimation can be only performed when the source is active which may happen only during showtime and this necessitates that the combining function be estimated in the presence of the useful data signal. In typical impulse noise scenarios, the SNR dips by around 10-40 dB though the data signal remains stronger than the impulse noise. Therefore estimation of the CM-DM noise cross-correlation needs a large number of DMT symbols to average out the stronger data signal. Faster estimation can be achieved if the useful data signal can be removed from the received DM signal but since detection in the presence of impulse noise will result in high number of decision errors, the data signal cannot be simply subtracted out. Methods based on reserved or pilot sub-carriers cannot be used since the length of the time domain CM-DM impulse response is typically of the order of a few hundred taps and therefore a large number of pilot sub-carriers will be needed. Existing works on CM based

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noise cancellation which can be used for showtime estimation are frequency domain methods like [11][12] and time domain normalized least mean squares (NLMS) method suggested in [7]. Time domain recursive least squares (RLS) [13] may also be used in place of NLMS and will provide much faster convergence at the cost of higher complexity. These methods ([11][12][7]) have slow convergence in the presence of the stronger useful data signal and rely on the repetitive nature of the noise and are therefore not suitable for transient noise cancellation. To the best of our knowledge, no methods have been proposed that address transient noise cancellation based on the common mode sensor.

In this paper we propose an iterative decision-directed method based on alternating minimization which can achieve partial cancellation within a single DMT symbol (useful for transient noise) and much faster convergence for near-optimal cancellation as compared to the existing methods for repetitive noise scenarios. Similar algorithms based on alternating minimization principle have been proposed for other contexts like blind channel estimation and data detection for OFDM and MIMO receivers [14][15]. The proposed method is based on a joint time-frequency domain formulation for the noise cancellation problem, motivated by the fact that the length of the time domain impulse response of the CM-DM coupling function is smaller than the length of the DMT symbol and frequency domain allows the use of decision-directed estimation. We demonstrate the cancellation performance of the algorithm via simulation using measured CM-DM coupling functions and discuss its convergence behavior.

Notations: Lowercase letters refer to time domain signals and uppercase refers to frequency domain signals. Matrices are referred to by bold non-italicized letters and vectors are denoted by bold italicized letters. $\mathbf{M}^{\dagger}$ refers to the Moore-Penrose inverse of $\mathbf{M}$.

II. System Model and Problem Formulation

A. System Model

We assume that the CM-DM impulse noise coupling can be modelled as an LTI finite impulse response (FIR) filter in time domain [7][10] and this impulse response denoted by $h(n)$ is L taps long. Let $x(n)$ be the cyclically extended time domain DMT modulated data signal and $h_d(n)$ be the M tap long impulse response of the direct channel between the CO transmitter and the CPE receiver. The time domain impulse noise in the CM and DM are denoted by $z_{cm}(n)$ and $z_{dm}(n)$ while $v_{cm}(n)$ and $v_{dm}(n)$ constitute the background AWGN noise at the two sensors. There also exists a reverse DM to CM coupling which results in the DM data signal $x(n)$ leaking into the CM. This leakage signal is extremely small in comparison to the received DM useful data signal (appx 50 dB attenuation) [7] (also confirmed by lab measurements) and therefore the performance gain from combining the two is also very small. The problem formulation can be modified to factor in this leakage data signal but since the performance gain is very small we ignore this leakage in our formulation for simplicity.

Therefore the received time domain signals in CM and DM, $y_{cm}(n)$ and $y_{dm}(n)$, are given by:

$$y_{cm}(n) = z_{cm}(n) + v_{cm}(n) \tag{1}$$

$$y_{dm}(n) = \sum_{k=0}^{k=M-1} h_d(k)x(n-k) + z_{dm}(n) + v_{dm}(n) \tag{2}$$

$$z_{dm}(n) = \sum_{k=0}^{k=L-1} h(k)z_{cm}(n-k) \tag{3}$$

A fast Fourier transform (FFT) of length $2N$ (where N is the number of DMT sub-carriers) is applied to both the CM and DM real-valued[1] time domain signal blocks, $y_{cm}(n)$ and $y_{dm}(n)$, resulting in corresponding complex valued hermitian-symmetric frequency domain signals. The frequency domain representation of the received signals, impulse noises and background noises are denoted by $\boldsymbol{Y_{cm}}$, $\boldsymbol{Y_{dm}}$, $\boldsymbol{Z_{dm}}$, $\boldsymbol{Z_{cm}}$, $\boldsymbol{V_{cm}}$, $\boldsymbol{V_{dm}}$ and are related as:

$$\boldsymbol{Y_{cm}} = \boldsymbol{Z_{cm}} + \boldsymbol{V_{cm}}, \tag{4}$$

$$\boldsymbol{Y_{dm}} = \mathbf{H_d}\boldsymbol{X} + \boldsymbol{Z_{dm}} + \boldsymbol{V_{dm}}, \tag{5}$$

where $\mathbf{H_d}$ is a diagonal matrix containing the circularly convolved frequency domain channel coefficients while $\boldsymbol{X}$ representing the transmit symbols is a complex valued vector consisting of odd-integers normalized according to the DMT constellation size for each tone.

By (3), we see that the impulse noise in the DM can be cancelled by estimating the convolution of $z_{cm}[n]$ and $h[n]$. We do not have the exact estimate of z_{cm}, instead we observe y_{cm} in the CM. We define $\mathbf{y_{con}} \in \mathbb{R}^{2N\times L}$ as the convolution matrix consisting of the time domain samples of y_{cm} as shown below.

$$\mathbf{y_{con}} = \begin{bmatrix} y_{cm}(0) & .. & .. & .. & y_{cm}(-(L-1)) \\ .. & .. & .. & .. & .. \\ y_{cm}(2N-1) & .. & .. & .. & y_{cm}(-(L-2N)) \end{bmatrix}$$

When $E\{z_{cm}^2(n)\} >> E\{v_{cm}^2(n)\}$, i.e. impulse noise in CM is much higher in power than the background noise, which is usually the case, $y_{cm}(n) \approx z_{cm}(n)$ and $\mathbf{W}\mathbf{y_{con}}\boldsymbol{h} \approx \boldsymbol{Z_{dm}}$. Hence by (5),

$$\boldsymbol{Y_{dm}} \approx \mathbf{H_d}\boldsymbol{X} + \mathbf{A}\boldsymbol{h} + \boldsymbol{V_{dm}} \tag{6}$$

where $\mathbf{A} = \mathbf{W}\mathbf{y_{con}}$ and $\mathbf{W} \in \mathbb{C}^{2N\times 2N}$ is the discrete Fourier transform (DFT) matrix. Since we observe $\mathbf{A}$, the impulse noise in the DM can be simply cancelled by subtracting $\mathbf{A}\boldsymbol{h}$ from $\boldsymbol{Y_{dm}}$, provided $\boldsymbol{h}$ is known.

[1] VDSL transmission is baseband, hence all the time domain signals are real-valued.

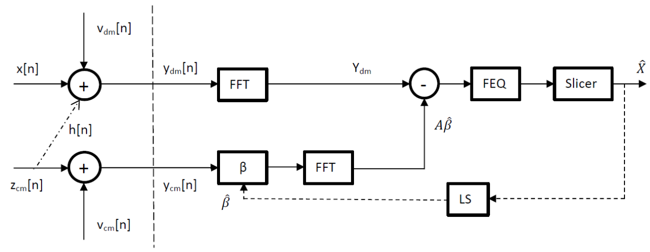

Fig. 1. Block diagram of the receiver with the proposed canceler

B. Problem Formulation

We propose a joint time-frequency domain framework where we combine a linearly convolved version of the CM signal with the DM signal before FEQ in order to cancel the impulse noise at the DM. Let the filter used for convolution be denoted by $\boldsymbol{\beta}$ whose length is set equal to the assumed length of $\boldsymbol{h}$ i.e. L taps. Motivated by (6), we consider the following optimization problem for detecting $\boldsymbol{X}$:

$$\underset{\boldsymbol{\beta},\boldsymbol{X}}{argmin} \parallel \mathbf{H_d^{-1}}(\boldsymbol{Y_{dm}} - \mathbf{A}\boldsymbol{\beta}) - \boldsymbol{X} \parallel_2^2 \tag{7}$$

with $\boldsymbol{\beta} \in R^L$ and $\boldsymbol{X}$ consisting of scaled complex odd integer values drawn from DMT constellations in use.

For the above problem, if $\boldsymbol{X}$ is given, estimating the combining function $\boldsymbol{\beta}$ is an over-determined least squares problem, if we assume $L << 2N$ (Corroborated by measurements, refer Section IV). In the absence of additive noise at the CM, its expected solution will be the CM-DM coupling function $\boldsymbol{h}$. If we assume that the optimal combining function $\boldsymbol{\beta}$ is available, the above problem is a near optimal estimator for $\boldsymbol{X}$ since the CM and DM background noises are assumed to be white Gaussian. The use of frequency domain DM signal in the formulation facilitates the use of decision-directed estimation to determine estimates of $\boldsymbol{X}$. Optionally, we may add frequency dependent weighting to the metric in (7) in the form of a diagonal weighting matrix $\mathbf{T}$. The motivation for weighting will be explained later. Thus the optimization problem is modified as:

$$\underset{\boldsymbol{\beta},\boldsymbol{X}}{argmin} \parallel \mathbf{T}(\mathbf{H_d^{-1}}(\boldsymbol{Y_{dm}} - \mathbf{A}\boldsymbol{\beta})) - \boldsymbol{X}) \parallel_2^2 \tag{8}$$

Problem (8) is a mixed optimization problem with decision variable $\boldsymbol{\beta} \in R^L$ and $\boldsymbol{X}$ being discrete. It can be converted to an integer LS problem thanks to a simple observation (similar to [16]). The optimal $\boldsymbol{\beta}$ which will minimize the cost function in (8) for any given $\boldsymbol{X}$ will satisfy the relation $\boldsymbol{\beta} = (\mathbf{TH_d^{-1}A})^{\dagger}\mathbf{T}(\mathbf{H_d^{-1}}\boldsymbol{Y_{dm}} - \boldsymbol{X})$. Thus (8) can be reformulated as

$$\underset{\boldsymbol{X}}{argmin} \parallel \boldsymbol{Y'_{dm}} - ((\mathbf{I} - \mathbf{P})\mathbf{T})\boldsymbol{X} \parallel_2^2 \tag{9}$$

where, $\mathbf{P} = \mathbf{TH_d^{-1}A}(\mathbf{TH_d^{-1}A})^{\dagger}$ and $\boldsymbol{Y'_{dm}} = ((\mathbf{I} - \mathbf{P})\mathbf{TH_d^{-1}})\boldsymbol{Y_{dm}}$ and $\boldsymbol{X}$ is discrete. Clearly, (9) represents an integer least squares problem. Sphere decoding [17] can be used to find an optimal solution to (9) but the complexity will be prohibitive considering the dimensions of the problem: $N = 4096$ and constellation sizes being very large (upto 2^{15}). VBLAST [17] uses a decision-directed approach to solve the problem but its complexity too is prohibitive. Therefore we attempt to use a lower complexity method to find a sub-optimal solution to the problem (8).

III. Algorithm Description

A. Steps

The proposed algorithm to solve (8) is motivated by the following:

- For a fixed $\boldsymbol{X}$, problem (8) is an over-determined LS problem in $\boldsymbol{\beta}$.
- For a fixed $\boldsymbol{\beta}$, problem (8) can be solved for $\boldsymbol{X}$ by a low complexity quantization (slicing) operation.

The proposed algorithm consists of alternating estimation of $\boldsymbol{X}$ and $\boldsymbol{\beta}$, starting with assuming $\boldsymbol{\beta^{(0)}} = \mathbf{0}$ and then using an iterative process to arrive at progressively better estimates of $\boldsymbol{X}$ and $\boldsymbol{\beta}$ using the same DMT symbol until the stopping condition is reached or a fixed number of iterations are completed. There are two steps in each iteration: a least squares estimation for $\boldsymbol{\beta}$ and a slicing operation for determining an estimate of $\boldsymbol{X}$. A formal description of the algorithm is given in Algorithm 1.

The proposed algorithm can be extended to multiple DMT symbol scenario by initializing $\boldsymbol{\beta}$ for the current symbol with the combining function estimate derived from the previous impulse noise affected DMT symbol and running Algorithm 1. For repetitive noise scenarios, running the algorithm for successive noise affected DMT symbols in this manner produces progressively better estimates of $\boldsymbol{\beta}$ and eventually achieves near optimal cancellation. This strategy is also useful for transient noise cases where impulse noise burst extends over several DMT symbols.

Algorithm 1 Processing over a single DMT symbol

Input: $\boldsymbol{Y_{dm}}$, $\mathbf{A}$ for current DMT Symbol
Initialize counter $k = 0$; $\boldsymbol{\beta}$ to zero i.e. $\boldsymbol{\beta}^{(0)} = 0$ OR $\boldsymbol{\beta}^{(0)}$ is inherited from previous DMT symbol
$\boldsymbol{X}^{(0)} = argmin \parallel \mathbf{T}(\mathbf{H_d^{-1}}(\boldsymbol{Y_{dm}} - \mathbf{A}\boldsymbol{\beta}^{(0)}) - \boldsymbol{X}) \parallel_2^2$ {Slicing}
repeat
    $k = k + 1$
    $\boldsymbol{\beta}^{(k)} = argmin_{\boldsymbol{\beta}} \parallel \mathbf{T}((\mathbf{H_d^{-1}}\boldsymbol{Y_{dm}} - \boldsymbol{X}^{(k-1)}) - \mathbf{H_d^{-1}A}\boldsymbol{\beta}) \parallel_2^2$ {Least Squares Estimate}
    $\boldsymbol{X}^{(k)} = argmin_{\boldsymbol{X}} \parallel \mathbf{T}(\mathbf{H_d^{-1}}(\boldsymbol{Y_{dm}} - \mathbf{A}\boldsymbol{\beta}^{(k)}) - \boldsymbol{X}) \parallel_2^2$ {Slicing}
until $\boldsymbol{X}^{(k)} = \boldsymbol{X}^{(k-1)}$ OR $k = R$, R: pre-selected value

B. Convergence Behavior

The alternating minimization steps over a single DMT symbol are guaranteed to lead to a decrease in the metric but there is no guarantee of achieving a global optimum. For the k^{th} iteration over a given DMT symbol, the two steps of the alternating minimization are as follows:

$$\boldsymbol{\beta}^{(\boldsymbol{k})} = \underset{\boldsymbol{\beta}}{argmin} \| \mathbf{T}(\mathbf{H_d^{-1}} \boldsymbol{Y_{dm}} - \boldsymbol{X}^{(\boldsymbol{k-1})} - \mathbf{H_d^{-1}} \mathbf{A} \boldsymbol{\beta}) \|_2^2 \quad (10)$$

$$\xi_1^{(k)} = \| \mathbf{T}(\mathbf{H_d^{-1}} \boldsymbol{Y_{dm}} - \boldsymbol{X}^{(\boldsymbol{k-1})} - \mathbf{H_d^{-1}} \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k})}) \|_2^2 \quad (11)$$

$$\boldsymbol{X}^{(\boldsymbol{k})} = \underset{\boldsymbol{X}}{argmin} \| \mathbf{T}(\mathbf{H_d^{-1}} (\boldsymbol{Y_{dm}} - \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k})}) - \boldsymbol{X}) \|_2^2 \quad (12)$$

$$\xi_2^{(k)} = \| \mathbf{T}(\mathbf{H_d^{-1}} (\boldsymbol{Y_{dm}} - \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k})}) - \boldsymbol{X}^{(k)}) \|_2^2 \quad (13)$$

Referring to (12) and (13), it can be seen that $\xi_2^{(k)} \leq \xi_1^{(k)}$ as $\| \mathbf{T}(\mathbf{H_d^{-1}} (\boldsymbol{Y_{dm}} - \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k})}) - \boldsymbol{X}^{(k)}) \|_2^2 \leq \| \mathbf{T}(\mathbf{H_d^{-1}} (\boldsymbol{Y_{dm}} - \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k})}) - \boldsymbol{X}^{(k-1)}) \|_2^2$. Similarly from (10) and (11), it can be inferred that $\xi_1^{(k)} \leq \xi_2^{(k-1)}$ as $\| \mathbf{T}(\mathbf{H_d^{-1}} \boldsymbol{Y_{dm}} - \boldsymbol{X}^{(\boldsymbol{k-1})} - \mathbf{H_d^{-1}} \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k})}) \|_2^2 \leq \| \mathbf{T}(\mathbf{H_d^{-1}} \boldsymbol{Y_{dm}} - \boldsymbol{X}^{(\boldsymbol{k-1})} - \mathbf{H_d^{-1}} \mathbf{A} \boldsymbol{\beta}^{(\boldsymbol{k-1})}) \|_2^2$. Therefore $\xi_2^{(k-1)} \geq \xi_1^{(k)} \geq \xi_2^{(k)}$ always holds and hence successive iterations over the same DMT symbol never lead to an increase in the error metric. The improvement in the error metric stops when the slicing step for the n^{th} iteration gives the same $\boldsymbol{X}$ as the $(n-1)^{th}$ i.e. $\boldsymbol{X}^{(\boldsymbol{n})} = \boldsymbol{X}^{(\boldsymbol{n-1})}$. There is no guarantee that the stopping condition coincides with the global optimum and the point of convergence cannot be predicted analytically.

At the first iteration of the algorithm, there will be bins with decision errors mixed up with bins having correct decisions from the slicer. At bins with decision errors i.e $X[q] \neq X^{(0)}[q]$, the term $X[q] - X^{(0)}[q]$ will be strongly correlated with the impulse noise $Z_{dm}[q]$ for that bin and therefore $Y_{dm}[q] - X^{(0)}[q] = X[q] - X^{(0)}[q] + Z_{dm}[q] + V_{dm}[q] \approx \alpha Z_{dm}[q]$ where α is a real number. We note that $\alpha = 1$ for bins with correct decisions and a higher fraction of the bins with incorrect decisions will have $\alpha > 0$ if the impulse noise on any bin is approximately modelled as complex Gaussian. Therefore, the over-determined least squares estimate for $\boldsymbol{\beta}^{(1)}$ will tend to push the solution towards achieving some positive cancellation which in turn tends to create more bins with correct decisions. In this manner, successive iterations over the same DMT symbol will tend to produce better estimates of $\boldsymbol{\beta}$.

A proof of convergence over multiple DMT symbols is beyond the scope of this paper and we demonstrate the same via simulation. In practice, the length of the impulse response of the CM-DM coupling is not known a-priori and we have to work with an assumed length L of the time domain cancellation filter $\boldsymbol{\beta}$. Too long an assumed length increases the complexity and may also affect the convergence speed while too short a length may lead to a loss in cancellation performance. A detailed analysis of the conditions for convergence of the algorithm for multiple DMT symbols and the dependency of the convergence behavior on the assumed length of the cancellation filter as well as the noise characteristics is part of the scope for future work.

C. Selecting the weights

The weights for each sub-carrier can be set equal to the channel attenuation for that frequency i.e. $T(q,q) = |H_d(q,q)|$ to counter the sensitivity introduced in the LS Estimation problem in (10) due to the poor conditioning of $\mathbf{H_d^{-1}}$ for loops where the higher frequency band experiences high attenuation.

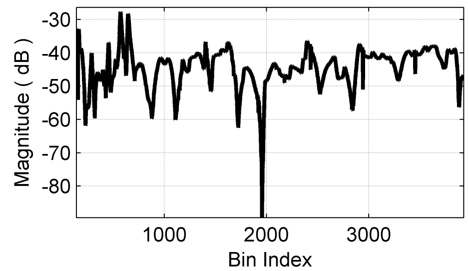

Fig. 2. Magnitude Frequency Response of measured CM to DM signal coupling

D. Dealing with banded VDSL FDD system

In a VDSL frequency division duplexed (FDD) system, the downstream (DS) receiver uses only a portion of the band. We tackle this case by setting $Y_{dm}[q] = 0$ for sub-carriers outside the DS bands, thus forcing the combining function estimate magnitude to near zero values outside the DS band. We may lower weights for these sub-carriers outside the DS band to avoid performance loss at the DS band edges.

E. Complexity

The complexity of the processing for a single DMT symbol is dominated by the step of estimating $\boldsymbol{\beta}$ which is of the order of $O(L^2N + L^3) \approx O(L^2N)$ multiplications while the additional per-iteration complexity is $O(NL)$ multiplications. In comparison VBLAST [17] has a complexity of $O(N^3)$, time-domain NLMS method in [7] has a complexity of $O(NL)$ while time-domain RLS has a complexity of the order of $O(L^2N)$ multiplications per DMT symbol.

IV. Simulation Results

We consider Prolonged Electrical Impulse Noise (PEIN) as well as Repetitive Electrical Impulse Noise (REIN) scenarios to verify the performance of the algorithm. The simulation parameters are described in Table I while the measured CM-DM coupling function is shown in Figure 2. The CM-DM coupling function has been measured by injecting white noise into the loop via a common mode signal injection circuit and the signal measured at both CM and DM sensors. The length of the impulse response of the measured CM-DM coupling function is around 1600 taps but the bulk of the energy is concentrated in around 500 taps. We therefore set the length of the combining function $\boldsymbol{\beta}$ to $L = 500$ taps in the proposed cancellation algorithm.

A. PEIN

We consider two PEIN scenarios: strong noise: Appx -90 dBm/Hz and moderate noise: Appx -120 dBm/Hz [1] for a 500m loop. The PEIN burst length is selected as 4 DMT symbols and PEIN is modelled as white Gaussian [1]. For

TABLE I
SIMULATION SETUP PARAMETERS

Loop Length	500m 26AWG
Length of DMT Symbol($2N$)	8192 Samples
Bandplan	VDSL 17A N. America
DM Background Noise	-140 dBm/Hz AWGN
CM Background Noise	-130 dBm/Hz AWGN
CM-DM Coupling Function used for generating DM Impulse Noise Signal	Measured(1600 Taps)
Assumed Length of combining function β	$L = 500$ Taps
Noise Margin , Coding Gain(TCM)	6 dB, 4 dB

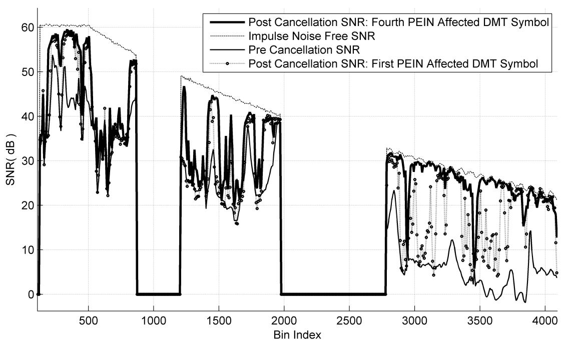

Fig. 3. PEIN Cancellation Performance with Impulse Noise: appx -120 dBm/Hz

the estimation algorithm we set the number of iterations per DMT symbol to be $R = 30$. Figures 3 and 4 show the cancellation performance of the algorithm for the 1^{st} and 4^{th} DMT symbols in the PEIN burst for the moderate and strong noise scenarios respectively. For the moderate noise case, the cancellation performance is very good in DS3 band which has bit-loading ranging from 5 to 8 bits per bin while the cancellation performance is marginal in the DS1 band which has bit-loading of 14-15 bits per bin. For the strong noise case, partial cancellation is achieved for all DS bands with SNR improvements ranging from 5-10 dB in DS1 band to over 20 dB in DS3 band.

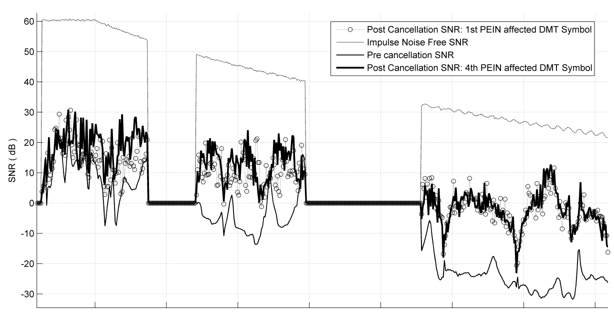

Fig. 4. PEIN Cancellation Performance with Impulse Noise: appx -90 dBm/Hz

B. REIN

We consider a REIN scenario with impulse noise modelled as white Gaussian noise with a approximate level of -120 dBm/Hz for a 500m loop. For the estimation algorithm we set the number of iterations per DMT symbol to $R = 3$ and run the algorithm over a sequence of 50 impulse noise affected DMT symbols. Figure 5 shows the resulting cancellation performance. It is seen that the proposed algorithm converges well to provide close to optimal cancellation for all bands while the time domain NLMS algorithm [7] doesn't achieve any appreciable cancellation and time domain RLS algorithm achieves partial cancellation in DS3 band only in the given 50 DMT symbol sequence.

Next we consider a REIN scenario with noise modelled as a twin narrow-band Gaussian signal, set the number of iterations per DMT symbol to $R = 10$ and run the algorithm over a sequence of 10 interference affected DMT symbols. Figure 6 shows the resulting cancellation performance. It is seen that almost complete cancellation is achieved in 10 DMT symbols for bins with high bit-loading (10 bits per bin) while near complete cancellation happens within 1 DMT symbol for bins with low bit-loading (5 bits per bin).

V. CONCLUSION

For PEIN scenarios, the proposed algorithm can provide partial to complete cancellation for regions with low bit-loading but the gains are smaller for regions with high bit-loading. For REIN scenarios, the proposed algorithm can achieve very rapid convergence as compared to the time domain RLS/NLMS algorithm. The algorithm also works well for poorly-conditioned excitation like narrow-band noise. The complexity of the algorithm is similar to time domain RLS but it opens up the possibility of mitigating transient impulse noise. The scope for future work on this problem includes reducing the complexity of the algorithm as well as a more detailed analysis of the convergence.

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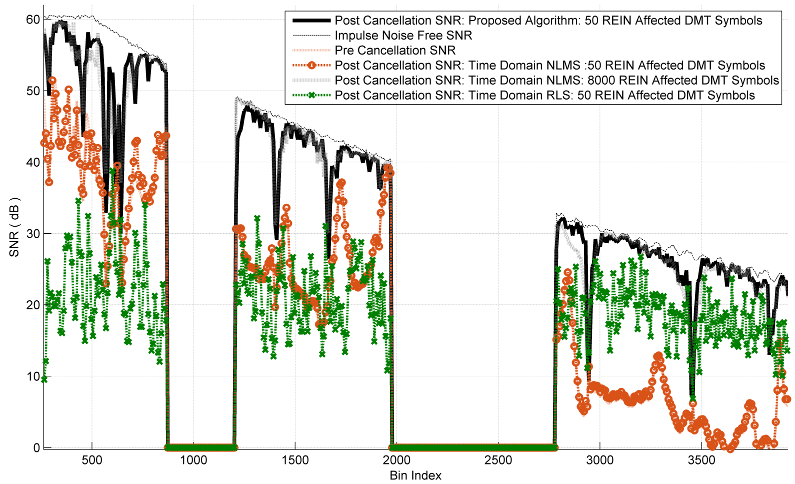

Fig. 5. REIN Cancellation Performance with Impulse Noise: appx -120 dBm/Hz

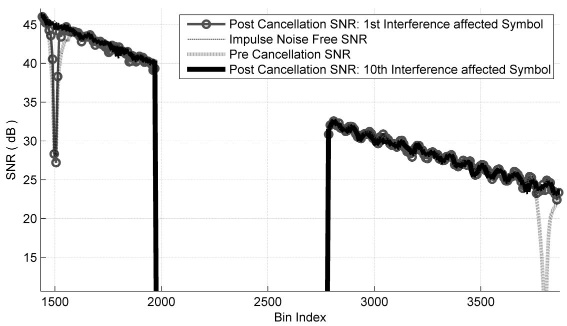

Fig. 6. Cancellation performance with narrowband interference

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