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# Convolutional Coded Bayesian Inference Based Channel Estimation in Power Line Communication Systems

Mohammad Asadpour
Electrical Department, University of Bonab, Velayat Highway, Bonab, East Azarbaijan, Iran-5551761167

***Abstract*—*Power line communication (PLC) channel as a medium for high speed data communication transmission based on orthogonal frequency division multiplexing (OFDM) is considered. It is an environment with frequency selective and multipath fading features which has been contaminated by impulsive noise. These deficiencies in power line communications degrade the accuracy of channel estimation. In this article, an efficient channel estimation method based on bayesian inference is presented. A new proposed kernel function with proper hyper-parameters in relevance vector machine (RVM) is used to estimate the PLC channel impulse response. Bit error rate for hard and soft decisions in Viterbi decoding corresponded to convolutional coded data and mean square error (MSE) are evaluated and compared. Proposed channel estimation algorithm achieves good results respected to recently reported approaches as Huang channel estimation method. It is shown that about 8dB improvement in MSE with respect to Huang method is achieved. Also, for bit error rate (BER=$10^{-3}$), about 2.2dB and 1.8dB enhancements in signal to impulsive and background noises ratio (SNIR) respected to Huang method with soft and hard decisions are obtained, respectively.*

***Keywords*—*Convolutional coding, impulsive noise, multipath effects, OFDM, power line communication, RVM.*

## I. INTRODUCTION

Power Line Communication (PLC) has been considered as a technology to transfer data over electrical power systems. Power lines exist in almost everywhere and there is no need for new communication wiring. Signal distortion due to frequency-dependent cable losses, multipath propagation caused by impedance mismatching and noises [1], [2] degrade the performance of PLC systems in high speed data communications. The stochastic changes of power line channel transfer function are caused by many phenomena such as load variations, number of branches and wire’s length in the network [3], [4]. The number of reflections between transmitter and receiver are determined by the number of branches which form network topology. Therefore, power line networks imitate a multipath propagation environment. To overcome multipath fading and noise effects, multi-carrier Orthogonal Frequency Division Multiplexing (OFDM), has been considered as an efficient modulation scheme to obtain high bit rate communications which can resolve Broadband Power Line (BPL)’s frequency selectivity [5], [6]. OFDM is more flexible for coding, constellation and power assignment which can be controlled per subcarrier [7]. In [8], Gunawan et al. have analyzed the performance of OFDM in PLC systems.

The pilot based algorithms such as Minimum Mean Square Error (MMSE) [9] and Maximum Likelihood (ML) [10] are traditional channel estimators that minimize a Least-Squares (LS) error function. These algorithms may not have optimum results when the noise deviates from a Gaussian distribution [11]. In order to improve the channel estimation performance of PLC system in the presence of impulsive noise, suitable algorithms are needed [12]-[15]. A comb-type pilot-based channel estimation in PLC systems was proposed in [16]. In [17] an optimized channel estimation algorithm based on a time-spread structure in OFDM low-voltage power line communication has been proposed. Chen et al. have employed a dual Gaussian interpolation method working on the amplitude and phase domain simultaneously, instead of the real and imaginary part in conventional schemes [18]. In [19] a sounding method for channel estimation based on a time synchronization technique has been used. Devri in [20] has applied an MLP neural network structure with the back propagation-learning algorithm for channel estimation. Another recently reported channel estimation approach with impulsive noise mitigation using compressive sensing technique has been taken into consideration for 1/2-rate coded-OFDM system [21].

An improved channel estimation technique based on IFFT and then de-noising has been proposed in [22]. Another channel estimation method as Huang has been defined a nonlinear cost function in order to reduce the impulsive noise effects in PLC [23]. In [24], a non-linear channel estimation for OFDM system by complex least square support vector machines (LS-SVM) under high mobility conditions has been introduced. Nassar et.al in [25] have used a factor graph approach to joint OFDM channel estimation and decoding in impulsive noise environments. In [26] an improved channel estimation approach in discrete multi-tone communication systems has been presented. It is based on sparse Bayesian learning relevance vector machine (RVM) in which a kernel as a Gaussian type function with additive white Gaussian noise based on real data has been considered.

In this paper, we apply our proposed RVM based algorithm to estimate the PLC channel. In order to decode the convolutional coded data, Viterbi decoding with hard and soft decisions is used. First, we improve the conventional RVM with Gaussian kernel to introduce RVM technique in complex domain. Next, we enhance the proposed method with a new kernel function and proper hyper-parameters which has more suitable fitting features with PLC channel impulse response to



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estimate the power line communication channel impaired with impulsive noise in OFDM system. Simulation results show that the proposed method outperforms to recently reported channel estimators.

The remainder of this paper is organized as follows. Section II briefly explains system model including OFDM systems, PLC channel and impulsive noise models. In Section III, our proposed channel estimation algorithm is presented. Section IV evaluates the performance of proposed methods respected to conventional RVM and Huang channel estimation approaches. Finally, conclusions are drawn in section V.

## II. System Model

### A. OFDM systems

OFDM scheme divides the effective spectrum to a number of orthogonal narrowband sub-channels. In other words, OFDM technique splits a frequency selective channel to a number of frequency flat sub-channels, in which, each sub-channel handles own data using individual subcarrier. The block diagram of OFDM system is shown in Fig. 1. In order to generate M-ary symbols, the binary inputs in transmitter are grouped. The result symbols are modulated by signal mapper sub-system. Then, the serial input symbols through a serial to parallel (S/P) sub-block are converted to a parallel data vector $X=[X_0, X_1 \ldots, X_{N-1}]$. The size of X in OFDM signal represents the number of subcarriers including data and pilots. To eliminate the ISI effect in OFDM signals, a guard time which well known as cyclic prefix must be added. The result OFDM signal after converting to serial form is transmitted through a frequency selective power line channel contaminated by impulsive noise. The receiver removes CP and after demodulation and channel estimation recovers data.

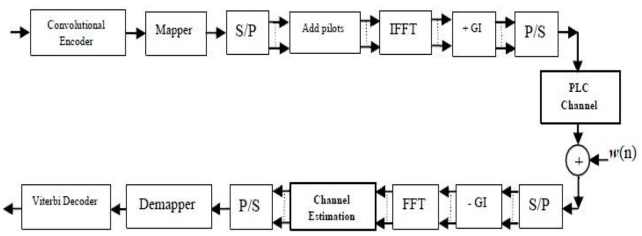


Fig. 1. OFDM block diagram.

### B. PLC channel model

The channel estimation based on extracted pilots is necessary at the receiver to equalize the received data. In this article, the estimation of power line communication channel contaminated by impulsive noise along with background noise is taken into consideration. Signals propagate in PLC network including direct path between transmitter and receiver as a main path and other branches connected to the system. These branches can create the reflected signals as echoes which can cause a multipath distortion. The result is considered as a frequency selective multipath fading model. Multipath models for power line channels have been proposed by Philipps [27] and Zimmermann [28]. In this paper we will use Zimmermann's model to describe PLC channel. This model involves the superposition of $N$ different paths with weight $g_i$ and length $d_i$ for each path $i$. Attenuation also can be modeled by the parameters $a_0$ , $a_1$ and $k$. Finally the multipath model for channel can be described by the following equation:

$$H(f)=\sum_{i=1}^{N}\underbrace{g_i}_{(1)}.\underbrace{e^{-(\alpha_0+\alpha_1.f^k).d_i}}_{(2)}.\underbrace{e^{-j2\pi f(d_i/v_p)}}_{(3)} \tag{1}$$

In (1), First term is corresponded to weight and the attenuation of channel is related to first exponential function and third term involves echo scenario. Propagation speed, $v_p$ depends on the speed of light $c_0$ and dielectric constant $\varepsilon_r$ of the insulating material of the cable which can be calculated as:

$$v_p=\frac{c_0}{\sqrt{\varepsilon_r}} \tag{2}$$

### C. Impulsive noise model

Unlike the most communication channels, power lines do not imitate Additive White Gaussian Noise (AWGN) channels. The interference due to colored broadband noise, narrowband interference and different types of impulsive disturbance is rather complicated. The result interference in PLC can be classified into five groups as colored background noise, narrowband noise, synchronous or asynchronous periodic impulsive noise with fundamental frequency (usually 50 or 60 Hz) and finally asynchronous a-periodic impulsive noise [1], [29]. It can ordinarily be assumed that the first three noise classes to be stationary in a few or long period of time as seconds, minutes and sometimes even for an hour, and may be supposed as background noise. The time variant characteristics during microseconds to milliseconds can be found in two last noise classes. Switching transients anywhere in power line network cause asynchronous impulsive occurrences and more errors in data transmission. Unlike AWGN, impulsive interferences are sparse and can be statistically described as Gaussian mixture (GM), Symmetric alpha stable (SαS) or Middleton class-A (MCA) [30]. In this article, we apply MCA to model the impulsive noise in PLC channel. The probability distribution function of noise is defined as follows [31]:

$$p_z(z)=\sum_{m=0}^{\infty}\frac{\alpha_m}{\sqrt{2\pi\sigma_m^2}}\exp(-\frac{z^2}{2\sigma_m^2}) \tag{3}$$

Where

$$\alpha_m=e^{-A}\frac{A^m}{m!} \tag{4}$$

The variance $\sigma_m^2$ in (3) is defined as:

$$\sigma_m^2=(\sigma_g^2+\sigma_i^2)\frac{(\frac{m}{A})+\Gamma}{1+\Gamma} \tag{5}$$

Where

$$\Gamma=\frac{\sigma_g^2}{\sigma_i^2} \tag{6}$$



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The parameters $\sigma_g^2$ and $\sigma_i^2$ in (5) and (6) are the power of background and impulsive noises, respectively. Therefore, $\Gamma$ is known as background to impulsive noise power ratio. The parameter A is called the overlap factor or the impulsive index). For large values of A, the noise PDF follows Gaussian distribution whereas for small ones, it is highly impulsive. A typical Middleton-class A noise with A=0.1 and $\Gamma = 0.002$ is shown in Fig. 2.

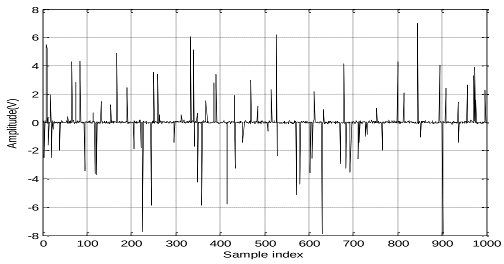


Fig. 2. Midddletone-class A noise, $\Gamma = 0.002$ , A=0.1

## III. PROPOSED METHOD

The performance of the estimation methods will be degraded by inaccurate estimation of the impulsive noise positions and therefore the optimum channel estimation will be required. LS algorithm is the simplest popular technique to estimate the channel which is usually degraded by AWGN and inter carrier interference (ICI).

Bayesian theory can be used to model the relevance vector machine (RVM) technique as a linear model with the marginal and conditional Gaussian distribution. The sparse distribution on weights in a Bayesian regression model using a suitable kernel function results to sparseness. The benefits of probabilistic predictions, automatic estimation of `nuisance' parameters and the facility to use any basis functions are the advantages accounted for RVM.

Usually, RVM predictions are modeled based on a function as $f(x)$ which can be defined over the input space [32]. Based on a linear combination of $M$ basic kernel functions as: $\boldsymbol{\varphi}(x)=(\varphi_1(x), \varphi_2(x), \ldots, \varphi_M(x))$, $f(x)$ can be obtained as follows:

$$f(x;w)=\sum_{i=1}^{M} w_i\varphi_i(x)=\boldsymbol{w}^T\boldsymbol{\varphi}(x) \tag{7}$$

Where $\boldsymbol{w}=(w_1, w_2, \ldots, w_M)^{\mathrm{T}}$ as a vector must be optimally estimated. In this method, learning the general models denoted by (7) is accomplished by a Bayesian probabilistic scheme.

In this article, our predictions will be based on RVM model. Therefore, we will define a new kernel function which plays an important role to get good results in channel estimation. The received complex-valued signals as an OFDM symbol will be used in RVM method to estimate the impulse response of the PLC channel in baseband model.

Our proposed block diagram shown in Fig. 3, will be used to estimate the multipath PLC channel based on a training sample of complex-valued functions. At first, an initial estimation of PLC channel is needed in RVM method which is done by traditional estimators, such as LS technique, using pilot based OFDM symbol as a training data. Two parallel paths in block diagram use RVM model on real and imaginary parts of the received input data. Concurrently, optimum initial values for necessary parameters are calculated to learn the RVM technique as well as possible. At the end of estimation, two parts of estimated channel response are merged to form the total and more actual complex-valued channel impulse response.

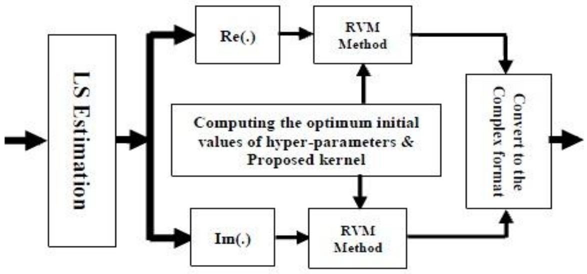


Fig. 3. Proposed block diagram.

In our method, a pseudo-random sequence as pilots, $X_p(n)$, (with $|X_p(n)|$=k ; for $n$ = 0, …,$N$-1), is applied. k is an adjustable amplitude of pilots which can control the local signal to noise ratio in the subcarrier locations and can save the transmitted power. The pilot symbols in receiver can be written as:

$$\mathbf{R}_p = \mathbf{X}_p\mathbf{H}_p + \mathbf{N}_p \tag{8}$$

Where $\mathbf{R}_p$ is the $N\times 1$ received pilot signal, $\mathbf{X}_p$ is the diagonal matrix of transmitted pilots, $\mathbf{N}_p$ is additive noise including the AWGN and impulsive noises in all pilot locations and $\mathbf{H}_p$ is pilot positioned frequency response of the channel. The estimation of channel frequency response in all subcarrier locations both pilot and data is main objective. It can be denoted by $H_m$ , ($m$ = 0, 1, 2,…, $N$-1) as the FFT of L unknown time samples, where L based on maximum delay spread is not further than the equivalent length of guard interval.

The initial channel estimation can be achieved by using (8) as follows [26]:

$$\begin{aligned}\tilde{\mathbf{H}}_p &= \mathbf{X}_p^H\mathbf{R}_p = \mathbf{X}_p^H\mathbf{X}_p\mathbf{H}_p + \mathbf{X}_p^H\mathbf{N}_p\\ &= k\mathbf{H}_p + \mathbf{N}_p^{/}\end{aligned} \tag{9}$$

Where $(.)^{\mathbf{H}}$ notation indicates the Hermitian-symmetric property. If the channel is assumed to be noise free then $\tilde{\mathbf{H}}_p$ can give the actual frequency response of the channel. In practice, however, $\tilde{\mathbf{H}}_p$ includes the channel which are degraded by the additive noises, $\mathbf{N}_p^{/}$. This is simply LS estimation and the following result can be obtained:

$$\mathbf{H}_{LS} = \frac{1}{k}\mathbf{X}_p^H\mathbf{R}_p = \frac{1}{k}\tilde{\mathbf{H}}_p \tag{10}$$

At the next step, IFFT of (9) results to the following equation in time domain:

$$\tilde{\mathbf{h}} = k\mathbf{h} + \mathbf{n}^{/} \tag{11}$$

Where $\tilde{\boldsymbol{h}} = [\tilde{h}_0, \tilde{h}_1, ..., \tilde{h}_{N-1}]^T$ , is the observation vector, $\boldsymbol{h} = [h_0, h_1, ..., h_v, 0, ..., 0]^T$ is the actual channel impulse response, and $\boldsymbol{n}' = [n'_0, n'_1, ..., n'_{N-1}]^T$ denotes additive noise vector with variance $\sigma'^2$.

Now, RVM algorithm based on sparse Bayesian regression model is applied to estimate $\boldsymbol{h}$ from the observations, $\tilde{\boldsymbol{h}}$. It sets a few regression weights to zero and as a consequence, the noise fitting in $\tilde{\boldsymbol{h}}$ is canceled. As in (7), the channel can be approximated using the function $f$ which is the linear combination of kernel functions as:

$$f(n) = \sum_i w_i \varphi(n-i) \quad (12)$$

This equation is the convolution of regression weight vector and kernel function which can be written in matrix form as follows:

$$\boldsymbol{f} = \boldsymbol{\phi w} \quad (13)$$

Where $\phi_{ij}=\varphi(i-j)$ is $(i, j)^{th}$ element of $\nu \times \nu$ kernel matrix and $\boldsymbol{w}$ is a column weights vector which includes $\nu$ entries. The more suitable kernel, the more sparse weight vector is resulted. In most researches, kernel $\phi(n)$ has been considered as a Gaussian function but in this paper we introduce a new kernel function with low complexity which has more correlative characteristics to PLC channel impulse response so that the best channel fitting and more sparsity of weight vector are obtained. A number of various impulse responses used in most references based on Zimmerman model [28] are shown in Fig. 4. It is clear that the suitable basic function as kernel in our proposed method is more compatible with triangle model. As a result, we propose the following basic kernel as a shifted triangle function:

$$\phi(n) = A \times \left| n + \frac{\text{v}}{4} \right| \quad (14)$$

Where $A$ is amplitude of proposed kernel and v is shift parameter which is needed to fit as much as possible in learning phase. In addition to proper fitting of this kernel with channel impulse response, it's complexity with respect to Gaussian kernel function in conventional RVM is significantly low.

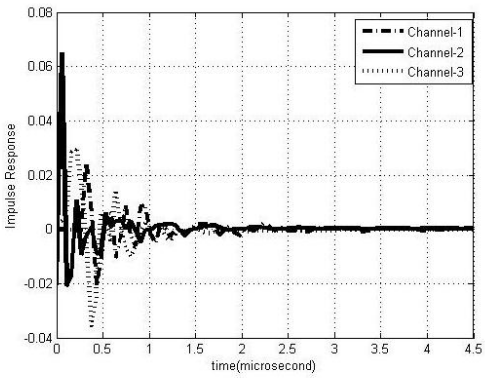


Fig. 4. Three types of channel impulse response.

Now applying the RVM method to the initial estimation of the channel as (11) can give the following equation.

$$\tilde{\boldsymbol{h}} = \boldsymbol{f} + \boldsymbol{e} = \boldsymbol{\phi w} + \boldsymbol{e} \quad (15)$$

This equation corresponds to (13), where $\boldsymbol{f}=[f_0, f_1, \ldots, f_\upsilon]^T$ is the approximation function and $\boldsymbol{e}=[e_0, e_1, \ldots, e_\upsilon]^T$ denotes the error vector in regression model. Impulsive noise based on section II, can be considered Gaussian with slightly error. Therefore, errors in (15) are assumed independent Gaussian random variables, with variance $\boldsymbol{\sigma}^2$ and zero mean which are identically distributed as follows:

$$p(\boldsymbol{e}) = \prod_{i=1}^{\upsilon} N(e_i \mid 0, \boldsymbol{\sigma}^2) \quad (16)$$

By using a flexible Gaussian prior over the weights $\boldsymbol{w}$ and Bayesian inference, (16) with individual hyper-parameter for each weight can be written as [32], [33]:

$$p(\boldsymbol{w}, \boldsymbol{\alpha}) = \prod_{i=1}^{\upsilon} N(w_i \mid 0, a_i^{-1}) \quad (17)$$

The posterior over the weights is then obtained from Bayesian rule:

$$p(\boldsymbol{w} \mid \tilde{\boldsymbol{h}}, \boldsymbol{\alpha}, \boldsymbol{\sigma}^2) = \mathrm{N}(\boldsymbol{w} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) \quad (18)$$

with

$$\boldsymbol{\Sigma} = (\boldsymbol{\phi}^T \boldsymbol{B \phi} + \boldsymbol{A})^{-1} \quad (19)$$

$$\boldsymbol{\mu} = \boldsymbol{\Sigma \phi}^T \boldsymbol{B} \tilde{\boldsymbol{h}} \quad (20)$$

Where $\mathbf{B}=\sigma^2\mathbf{I}_\upsilon$, $\mathbf{A}=\mathrm{diag}(\alpha_0, \alpha_1, \ldots, \alpha_\upsilon)$ and $\mathbf{I}_\upsilon$ is the $\nu \times \nu$ identity matrix. By integrating out the weights, the marginal likelihood for $\boldsymbol{\alpha}, \boldsymbol{\sigma}^2$ is obtained:

$$p(\tilde{\boldsymbol{h}} / \boldsymbol{\alpha}, \boldsymbol{\sigma}^2) = N(\tilde{\boldsymbol{h}} / \boldsymbol{0}, (\boldsymbol{B}^{-1} + \boldsymbol{\phi A}^{-1} \boldsymbol{\phi}^T)) \quad (21)$$

The result regression estimation is given by $\boldsymbol{h}_{\mathrm{RVM}}=\boldsymbol{\phi\mu}$ where $\boldsymbol{\alpha}$ and $\sigma$ can be computed by maximizing the conditional probability as $p(\boldsymbol{\alpha}, \boldsymbol{\sigma}^2 / \tilde{\boldsymbol{h}})$. The maximum likelihood of (21) is corresponding to the maximum of $p(\boldsymbol{\alpha}, \boldsymbol{\sigma}^2 / \tilde{\boldsymbol{h}})$ when hyper-prior is uniform assumed [32]. The maximum value of (21) respected to $\boldsymbol{\alpha}$ and $\sigma^2$ can be obtained as follows [34]:

$$\alpha_i^{new} = \frac{\gamma_i}{\mu_i^2} \quad (22)$$

and

$$\sigma_{new}^2 = \frac{\| \boldsymbol{t} - \boldsymbol{\phi\mu} \|^2}{\upsilon - \sum_i \gamma_i} \quad (23)$$

Where $\mu_i$ is the i'th weight of posterior mean given by (20) and $\gamma_i = 1 - \alpha_i \Sigma_{ii}$. $\Sigma_{ii}$ is the i'th diagonal element of the posterior weight covariance matrix based on current $\boldsymbol{\alpha}$ and $\sigma$ values. In this algorithm, the initial values of the hyper-parameters for convergence of the learning process and proper performance are very important. We determine jointly the values of $\boldsymbol{\alpha}$ and $\sigma$ based on MMSE criterion. This is similar to Expectation-Maximization (EM) algorithm [34] that proceeds based on the flowchart shown in Fig. 5.

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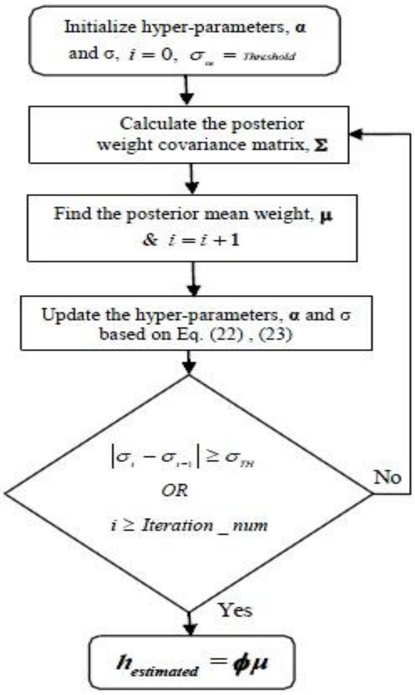


Fig. 5. Proposed algorithm flowchart

## IV. SIMULATION RESULTS

Use To evaluate the performance of the proposed method applied to PLC channels, computer simulations are carried out based on parameters in Table 1. Also, PLC channel model in all simulations is characterized by the parameters in Table 2, which is modeled by zimmermann multipath model as (1) [28]. At first, we apply our proposed channel estimation algorithm to compute BER and MSE criteria respected to various SNIR values. SNIR is the ratio of signal to impulsive and background noises which is defined as follows:

$$SNIR = \frac{P_S}{(1-p)P_N + p.P_I} \tag{24}$$

Where $P_S$, $P_N$ and $P_I$ are the powers of transmitted signal, background white Gaussian noise and impulsive noise, respectively. The parameter p controls the effects of impulsive and background noises.

TABLE I. Simulation parameters.

| Parameter | Value |
|---|---|
| Encoder | Convolution |
| Decoder | Viterbi (Soft & Hard |
| Number of | 64,128, 360, 3072 |
| FFT size | 256, 512, 4096 |
| Pilot spacing | 4 |
| Size of Cyclic | 64, 512 |
| Baseband | BPSK, QPSK |
| Channel type | PLC(AWGN + Impulsive |

After proposing triangle model for kernel, it is demonstrated the effects of initial values of the hyper-parameters $\boldsymbol{\alpha}$ and σ. Fig. 6, shows the MSE respected to the initial values of these hyper-parameters. It is shown that there are at least two local minimums and the optimum values in the steady state should be chosen in Fig. 6, as: $\alpha_i = 8\times10^{-7}$, $\sigma = 0.35$.

TABLE II. Parameters of four-path model.

| Attenuation parameters | | |
|---|---|---|
| K | $a_0$=0 | $a_1$=7.8×$10^{-10}$ s/m |
| **Path parameters** | | |
| **i** | **$g_i$** | **$d_i$/m** |
| 1 | 0.64 | 200 |
| 2 | 0.38 | 222.4 |
| 3 | -0.15 | 244.8 |
| 4 | 0.05 | 267.5 |

Fig. 7 shows MSE criterion of channel estimation techniques in the presence of impulsive noise effects. As seen, for BPSK modulation and 64 subcarriers, about 4 dB improvement in MSE of our proposed algorithm respected to Huang method is achieved.

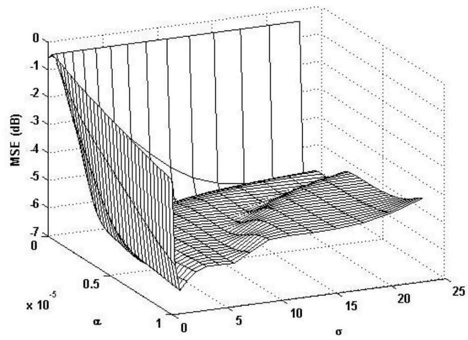


Fig. 6. MSE respected to the hyper-parameters variation.

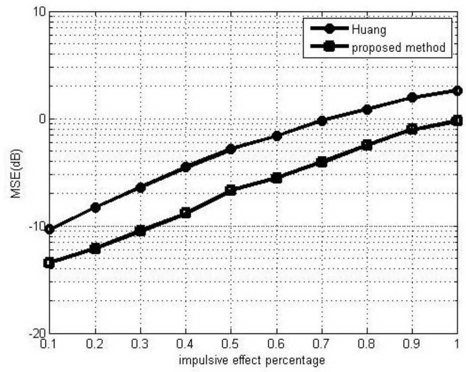


Fig. 7. Impulsive noise effects, BPSK, N=256, Nc=64, CP=64, Pilot space=4

Fig. 8, compares MSE performance of our proposed method with Huang and improved complex RVM approaches, for 3072 subcarriers and 512 cyclic prefix size according to

PLC standard P1901 [35]. For instance, for SNIR=7dB, about 8dB and 10dB improvements in our proposed technique with respect to complex RVM and Huang methods are obtained, respectively.

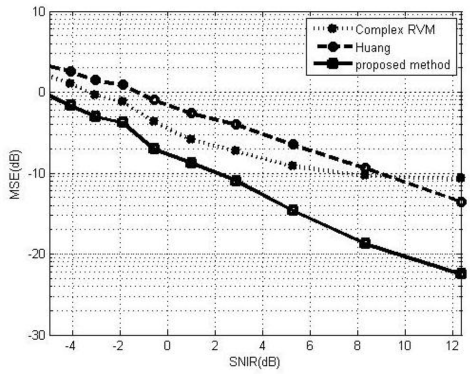


Fig. 8. MSE comparison, BPSK, N=4096, Nc=3072, CP =512, Pilot space=4

In order to improve the channel capacity, forward error correction (FEC) is needed which is done by adding some carefully designed redundant information to the data being transmitted through the channel. The process of adding this redundant information is known as channel coding. Convolutional coding is one of the two major forms of channel coding. There are a variety of useful convolutional codes and a variety of algorithms for decoding the received coded information sequences to recover the original data. Convolutional codes are usually described using two parameters: the code rate and the constraint length. The code rate, k/n, is expressed as a ratio of the number of bits into the convolutional encoder (k) to the number of channel symbols output by the convolutional encoder (n) in a given encoder cycle. The constraint length parameter, K, denotes the "length" of the convolutional encoder. Viterbi decoding is one of the two types of decoding algorithms used with convolutional encoding. In this paper, convolutional encoder using Viterbi decoder with hard and soft decisions is applied to our proposed algorithm. Fig. 9 compares the results due to proposed algorithm with Huang method in three conditions: uncoded, hard and soft decisions Viterbi decoding for 128 subcarriers, CP=64 and BPSK modulation. The convolutional encoder in these simulations has code rate ½, constraint length of the code, 7 and generator polynomial matrix, [171 133]. Results show the appropriate improvements of our proposed method respected to the Huang and any uncoded methods. For example, for BER=$10^{-3}$ in soft decision decoding, about 6dB and 2.5 dB SNIR improvements of our method respected to uncoded and Huang methods are achieved, respectively. For hard decision, about 1.6dB enhancement of our method with respect to Huang is obtained. Fig. 10 shows the results for QPSK modulation. Other parameters are as the same of Fig. 10. About 2dB and 2.2db improvements are achieved for hard and soft decisions, respectively.

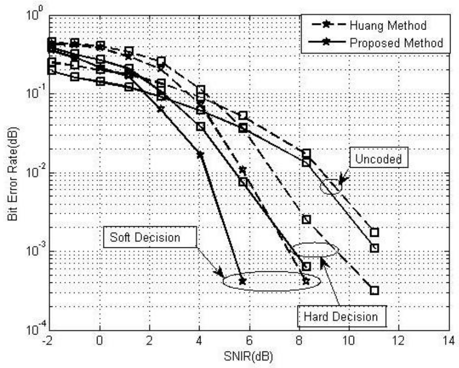


Fig. 9. BER comparison, BPSK, N=512, Nc=128, CP =64, Pilot space=4

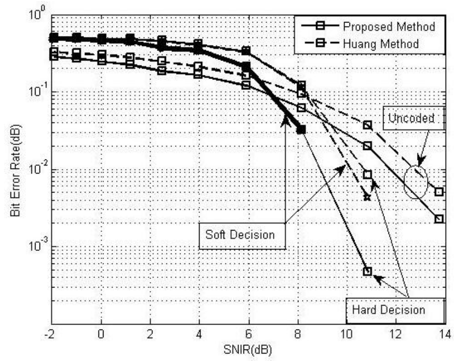


Fig. 10. BER comparison, QPSK, N=512, Nc=128, CP =64, Pilot space=4

## V. CONCLUSION

In this article, it was proposed new kernel with optimum hyper-parameters in relevance vector machine method. Also the complex-valued analysis based on RVM was used to estimate the power line communication channel. Our proposed algorithm caused good enhancements in the obtained channel estimation results. It was shown that MSE and BER parameters of our proposed method have good results in any conditions. Also the increasing of impulsive noise effect in our proposed method was compared with recently reported methods as Huang and improved conventional RVM with Gaussian kernel function. The robustness of our method against to impulsive noise effects was completely proved. Finally, in order to improve the channel capacity, convolutional coding along with viterbi decoding as an FEC technique was applied to our algorithm. The obtained BER results confirm more considerable improvements of proposed method respected to the others.

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