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A robust Bayesian inference-based channel estimation in power line communication systems contaminated by impulsive noise

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Abstract: Broadband power line communication based on an orthogonal frequency division multiplexing scheme is considered in this paper. In addition to multipath fading and frequency selectivity, the power line communication channel is influenced by impulsive noise. More bit errors in power line communications are caused by these effects. In this paper, a relevance vector machine (RVM) is applied to the received complex data in order to estimate the power line communication channel impulse response in a baseband model. The bit error rate and mean squared error (MSE) performances under the impulsive noise and multipath effects are analyzed. It is shown that introducing a new kernel can increase the robustness of the proposed method against the critical effects of impulsive noise and multipath with low complexity. It is also shown that applying proper values to hyperparameters based on the minimum mean square error criterion can increase convergence speed and decrease MSE in our proposed method. Experimental results show the better performance of proposed algorithm compared to recently reported methods such as the Huang method and conventional RVM with Gaussian kernel function in complex mode, namely complex RVM.

Key words: Power line communication, impulsive noise, orthogonal frequency division multiplexing, kernel, multipath effects, relevance vector machine, hyperparameters

1. Introduction

Power line communication (PLC) has been introduced as a technology in which data are transmitted over electrical power systems. Power lines exist almost everywhere and there is no need for any communication wiring. The primary simple reported applications based on PLC were remote voltage monitoring in telegraph systems and remote meter reading [1]. Nowadays, power lines as transmitting media for data, voice, and video are taken into consideration. PLC systems play important roles in broadband services [2–4] and smart grid applications [5,6] due to the ubiquity of power lines and power outlets.

There are many problems in power line networks such as signal distortion due to frequency-dependent cable losses, multipath propagation caused by impedance mismatching, and noise, which degrade the performance of PLC systems in high-speed data communications. The noise characteristics of power line networks were analyzed in [7,8]. Most researchers have also pointed out that the stochastic changes of power line channel transfer function are due to many phenomena such as load variations, number of branches, and the wire's length in the network [9,10]. In addition, a PLC channel is a rough and noisy environment, which cannot be modeled in a simple form. It is a time-variant channel with frequency selectivity features that is contaminated by various kinds of noise, especially impulsive noise [11,12]. The transfer function of a PLC channel depends

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on variable network topology due to switched-on or -off electrical devices. The number of reflections between the transmitter and receiver are determined by the number of branches that form the network topology. Thus, power line networks are characterized as a multipath propagation environment. To overcome multipath fading and impulsive noise effects, a well-known multicarrier technique, orthogonal frequency division multiplexing (OFDM), has been considered as an efficient modulation scheme to obtain high bit rate communications that can resolve the BPL's frequency selectivity [13,14]. It has also high degree of flexibility for coding, constellation, and power assignment, which can be controlled per subcarrier [15]. In [16], Gunawan et al. analyzed the performance of OFDM in PLC systems.

In the OFDM technique, channel state information (CSI) is very important, which can be calculated by channel estimators in the receiver. This is usually done by pilot-based channel estimation techniques. The pilot-based algorithms such as minimum mean square error (MMSE) [17] and maximum likelihood [18] are traditional estimators that minimize a least-squares (LS) error function. These algorithms may not have optimum results when the noise deviates from a Gaussian distribution [19]. In order to improve the estimation performance in PLC channels influenced by impulsive noise, more suitable algorithms are needed [20–23]. When the classical estimation techniques fail, robust estimation algorithms can be applied [24,25]. Bueche et al. proposed a method for evaluating the performance of comb-type pilot-based channel estimation in PLC systems [26]. In [27], an optimized channel estimation algorithm based on a time-spread structure in an OFDM low-voltage PLC system was proposed. Chen et al. employed a dual Gaussian interpolation method working on the amplitude and phase domain simultaneously, instead of the real and imaginary parts in conventional schemes [28]. They used the channel models proposed by the Open PLC European Research Alliance for simulation. In [29], a sounding method for channel estimation based on a time synchronization technique was used. Devri applied an MLP neural network structure with a backpropagation learning algorithm for channel estimation [30]. The OFDM symbols consist of complex signals whereas a neural network uses real signals. Hence, complex signals are separated into real and imaginary parts to adopt the neural network to OFDM.

Another recently reported channel estimation approach with impulsive noise mitigation using a compressive sensing technique was taken into consideration for a 1/2-rate coded-OFDM system [31]. In [32], an approach based on Huber cost function was proposed to estimate the PLC channel. In [33], the SVM technique was applied to OFDM-based channel estimation. Due to the large computational complexity of the SVM, it is unfeasible for practical systems. In [34], an improved channel estimation approach in discrete multitone communication systems was presented. It was based on a 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 was considered.

In this paper, first we improve the conventional RVM with Gaussian kernel to introduce a complex RVM technique. Next we enhance the complex RVM method with a new kernel function that has more suitable fitting features with PLC channel impulse response and optimize its hyperparameters based on the MMSE criterion to estimate the PLC channel impaired with impulsive noise in an OFDM system. Simulation results show that the proposed method outperforms recently reported channel estimators.

This paper is organized as follows. In Section 2, the background material as OFDM system, PLC channel model, noise model in PLC channels, channel estimation, Huang channel estimation method, and RVM technique are presented. In Section 3, the proposed method is detailed. Section 4 is concerned with obtained simulation results. Finally, main conclusions are outlined in section 5.

2. Background material

2.1. OFDM system

Power line channels due to various branches with different loads connected to PLC networks are known as a multipath fading environments, similar to wireless channels. In terms of connected loads and branches, delayed signals interfere with the original signal and cause an intersymbol interference (ISI) distortion, which influences the performance of the network. OFDM based on parallel transmission of broadband data can solve this problem. It reduces the multipath effects and removes any equalizers or uses a simple first-order equalizer. It is mainly used in many wireless and wired applications, such as the asymmetric digital subscriber line [35], WIMAX technology, and high-speed communication networks [36].

OFDM as a multicarrier modulation scheme splits high data rate streams to lower rates, which are transmitted through narrowband flat subchannels. Indeed, the OFDM technique changes a frequency-selective channel to frequency-flat subchannels by splitting the effective bandwidth to orthogonal narrow subbands. Each subchannel including an individual subcarrier handles its own data. ISI can also be eliminated when a guard interval is used. The OFDM technique is not only robust against multipath fading and has a high spectral efficiency, but it also needs a simple channel equalization and its computational complexity is low [37]. The block diagram of the OFDM system is shown in Figure 1 and a guard interval is appended in Figure 2 to overcome the ISI effect in any OFDM system.

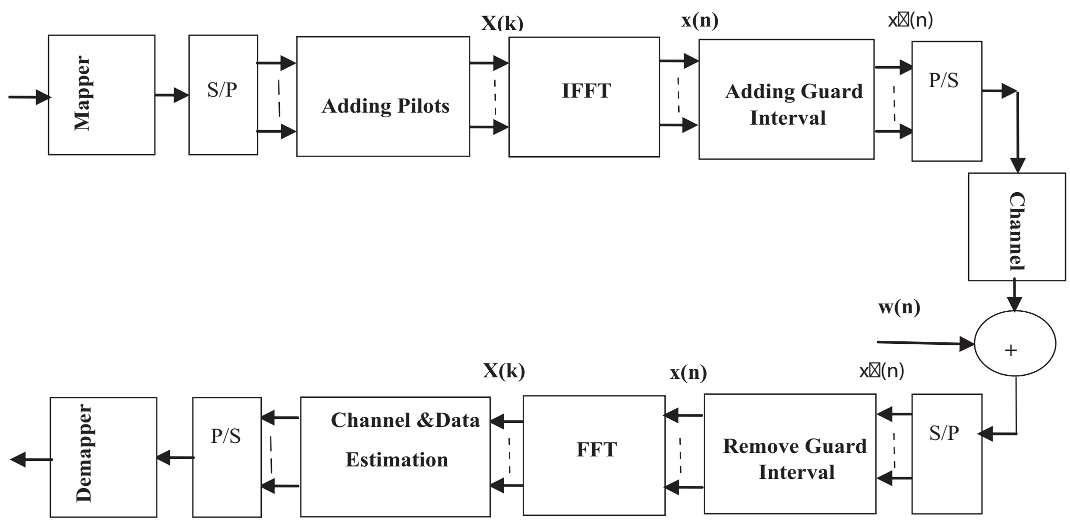

Figure 1. OFDM block diagram.

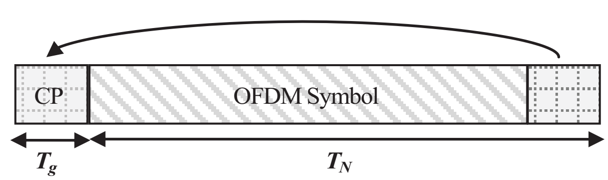

Figure 2. The OFDM symbol after the cyclic prefix addition.

At the receiver, channel estimation based on extracted pilots is necessary to equalize the received data. In this article, the estimation of a PLC channel contaminated by impulsive noise along with background noise is taken into consideration.

2.2. PLC channel model

Signals propagate in the PLC network including the direct path between the 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 were proposed by Philipps [38] and Zimmermann and Dostert [39]. In this paper, we will use Zimmermann and Dostert's model to describe the PLC channel. This model involves the superposition of N different paths with weight g_i and length d_i for each path i. All reflection and transmission factors, g_i, in power lines are basically less than or equal to one. Indeed, the load of the branch connection of two or more cables leads to impedance lower than the characteristic impedance of the feeding cable. Additionally, attenuation can be modeled by the parameters a_0, a_1, and k. Hence, the multipath model for the channel can be described by the following equation:

$$H(f) = \sum_{i=1}^{N} g_i . e^{-(a_0 + a_1 f^k) d_i} . e^{\frac{-j2\pi f d_i}{v_p}} \tag{1}$$

This equation represents a general form of the transfer function of power line channels. The attenuation of the channel is related to the first exponential function and the second one involves an echo scenario. Propagation speed ν_p depends on the velocity of light, c_0, and dielectric constant, ε_r, of the insulating material of the cable, which can be calculated as:

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

2.3. Noise model in PLC channels

Transmission characteristics and the interference phenomenon are important issues in PLC channels. Unlike most communication channels, power lines do not imitate additive white Gaussian noise (AWGN) channels. Colored broadband noise, narrowband interference, and different types of impulsive disturbance are rather complicated. The resulting 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 asynchronous aperiodic impulsive noise [7,40]. It can ordinarily be assumed that the first three noise classes are stationary in a short or long period of time as seconds, minutes, and sometimes even for an hour, and they may be supposed as background noise. The time-variant characteristics during microseconds to milliseconds can be found in the two last noise classes. The presence of these impulses in the transmission lines considerably increases the power spectral density of noise. Finally, there are usually a bit or more errors in data transmission. Switching transients anywhere in the power line network cause asynchronous impulsive occurrences. The shape of impulses is often similar to damped sinusoid signals or superimposed damped sinusoids. Time-domain representation of two examples is shown in Figure 3.

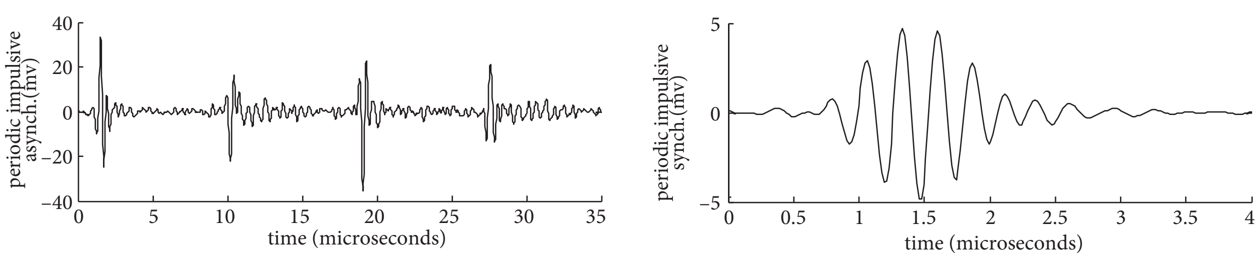

Figure 3. Time-domain representation of two impulsive events.

2.4. Channel estimation

A power line is a noisy transmission medium that is contaminated by Gaussian background noise and impulsive events. The performance of channel estimation methods is degraded by inaccurate estimation of impulsive noise positions. Therefore, optimum channel estimation is required. Channel estimation based on OFDM systems is generally performed in the frequency domain. Training data as pilot symbols are used by these estimation techniques to sample the channel transfer function.

2.4.1. Pilot-based channel estimation

Two basic 1D channel estimators in an OFDM system are illustrated in Figure 4. The first one is block-type, which is developed to estimate the channel including slow fading. It is performed by inserting pilot tones into all subcarriers of OFDM symbols within a specific period as time coherency. The second one, comb-type pilot channel estimation, is introduced to satisfy the need for equalizing the fast fading channel. It is accomplished by inserting pilot tones into predefined subcarrier locations. The pilot subcarrier spaces are determined by the frequency coherency in this arrangement. In this case, an interpolation technique must be used to estimate the channel gains in unknown data subcarrier positions. Parameters T_c and B_c in Figure 4 show time and frequency coherency of the channel, respectively.

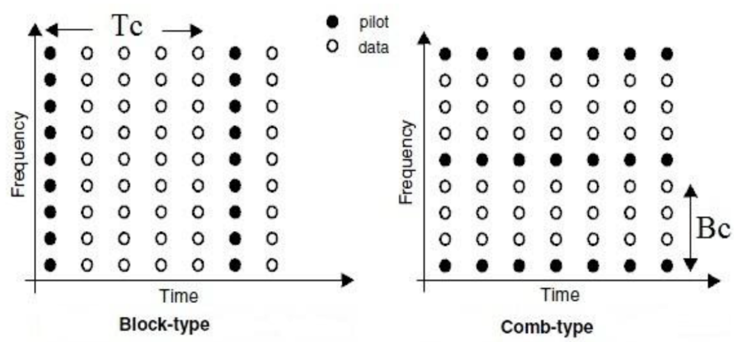

Figure 4. Two basic types of pilot arrangement based on OFDM channel estimations.

The LS algorithm is the simplest popular technique to estimate channel. It is usually degraded by AWGN and intercarrier interference. The estimated channel in this method can be simply written as:

$$H^{LS} = [\frac{y_0}{x_0}, \frac{y_1}{x_1}, ..., \frac{y_{N-1}}{x_{N-1}}] \tag{3}$$

Here, x_k and y_k represent transmitted and received data subcarriers for a kth symbol in OFDM, respectively. In [41], an improved channel estimation technique based on IFFT and then denoising was proposed.

2.4.2. A brief review of the Huang method

The received signal in multicarrier systems can be described as in Eq. (4) [32]:

$$y_n = \frac{1}{N} \sum_{k \in K_p} X_p(k) H(k) e^{j\frac{2\pi}{N}kn} + z_n \tag{4}$$

Here, z_n including e_n as a residual noise and the effects of unknown data symbols can be written as in Eq. (5).

$$z_n = \frac{1}{N} \sum_{k \notin K_p} X_s(k) H(k) e^{j\frac{2\pi}{N}kn} + e_n \tag{5}$$

Pilot and data symbols and the channel characteristic function in these equations are denoted by $X_p(k)$, $X_s(k)$, and $H(k)$, respectively. In this method, the received unknown data symbols are also considered as a noise. Based on the channel impulse response denoted by $h(n)$, Eq. (4) can be rewritten as:

$$\begin{aligned} y_n &= \tfrac{1}{N} \sum_{k \in K_p} X_p(k) \Big(\sum_{m=0}^{L-1} h(m) e^{-j\frac{2\pi}{N}km}\Big) e^{j\frac{2\pi}{N}kn} + z_n \\ &= \tfrac{1}{N} \sum_{k \in K_p} X_p(k) e^{j\frac{2\pi}{N}kn} \Big(\sum_{m=0}^{L-1} h(m) e^{-j\frac{2\pi}{N}km}\Big) + z_n \end{aligned} \tag{6}$$

This equation can be summarized in matrix form as follows:

$$\mathbf{Y} = \mathbf{Bh} + \mathbf{Z} \tag{7}$$

Here, $\mathbf{Y} = [\mathrm{y}_0, \mathrm{y}_1, \ldots, \mathrm{y}_{N-1}]^T$, $\mathbf{Z} = [\mathrm{z}_0, \mathrm{z}_1, \ldots, \mathrm{z}_{N-1}]^T$, and $\mathbf{B}$ is an $N \times L$ matrix with the following elements:

$$[B]_{n,m} = \frac{1}{N} \sum_{k=0}^{N_p-1} X_p(k) e^{j\frac{2\pi}{N} i_k (n-m)} \tag{8}$$

Here, $0 \le m \le L-1, 0 \le n \le N-1$.

The LS method cannot give an optimal result in PLC channel estimation because there is an impulsive noise in z_n. Therefore, a new cost function has been defined as in Eq. (9) [19]:

$$J(\rho) = \sum_{n=0}^{N-1} \rho(z_n) \tag{9}$$

Here, $\rho(.)$ is a nonlinear cost function in order to reduce the impulsive noise effects.

Substituting Eq. (7) in Eq. (9) and minimizing the cost function with respect to $\boldsymbol{h}$ using $\frac{\partial J}{\partial h} = 0$, the following equation in matrix form will be obtained [32]:

$$\hat{\mathbf{h}} = (\mathbf{B}^T \mathbf{Q} \mathbf{B})^{-1} \mathbf{B}^T \mathbf{Q} \mathbf{Y} \tag{10}$$

Here, $\mathbf{Q} = \mathrm{diag}(q(z_0),\ q(z_1),\ \ldots,\ q(z_{N-1}))$ with $q(z)$ defined as follows.

$$q(z) = \begin{cases} 1 & |z| \le \beta \\ \beta sgn(z)/z & |z| \ge \beta \end{cases} \tag{11}$$

β is a cut-off factor that can be computed by the median of z_n as $\beta = \varepsilon \times \mathrm{Median}(z_n)$, in which ε is a manually tuned parameter.

Since matrix $\mathbf{Q}$ in Eq. (10) is unknown, this estimator is modified with the following steps:

1) Find an initial estimate of $\boldsymbol{h}$ using the LS method as $\tilde{\mathbf{h}} = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T\mathbf{Y}$.

2) Obtain $\mathbf{z}$ by substituting the initial estimation in Eq. (7); therefore, $\mathbf{Z} = \mathbf{Y} - \mathbf{B}\tilde{\mathbf{h}}$.

3) Calculate matrix $\mathbf{Q}$ based on the obtained $\mathbf{z}$.

4) Calculate the final estimation of the channel using Eq. (10) in the time domain.

2.4.3. Review of the RVM method

Bayesian theory can be used to model the RVM technique as a linear model with marginal and conditional Gaussian distribution. The sparse distribution on weights in a Bayesian regression model using a suitable kernel function results in sparseness. Based on probabilistic Bayesian learning, accurate prediction models with less basis functions than a comparable SVM can be obtained [42]. The benefits of probabilistic predictions, automatic estimation of nuisance parameters, and the facility to use any basis functions are other additional advantages for RVM. Usually, RVM predictions are modeled based on a function as $f(x)$, which can be defined over the input space [42]. Based on a linear combination of M basic kernel functions as $\phi(x) = (\phi_1(x),\ \phi_2(x),\ \ldots,\ \phi_M(x))$, $f(x)$ can be obtained as follows:

$$f(x;w) = \sum_{i=1}^{M} w_i\varphi_i(x) = \mathbf{w}^T\varphi(x) \tag{12}$$

Here, $\boldsymbol{w} = (w_1,\ w_2,\ \ldots,\ w_M)^T$ is a weight vector that must be optimally estimated. In this method, learning the general models denoted by Eq. (12) is accomplished by a Bayesian probabilistic scheme.

3. Proposed method

In this article, our predictions will be based on a RVM model to estimate the PLC channel. We will define a new kernel function that plays an important role in getting good results in channel estimation. Recent reported studies of RVM-based channel estimation show that the RVM technique has been applied to real input data. In this paper, the received complex-valued signals as OFDM symbols will be used in the RVM method to estimate the impulse response of the PLC channel in a baseband model.

The block diagram of our proposed method is shown in Figure 5 and it will be used to estimate the multipath PLC channel based on a training sample of complex-valued functions. First, an initial estimation of the PLC channel based on traditional estimators, such as the LS technique, is obtained by using pilot-based OFDM symbols as training data. Two parallel paths in the block diagram use the 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. In our proposed method, a pseudorandom sequence is applied as pilots, $X_p(n)$, (with $|X_p(n)|=\mathrm{k}$; for $n = 0, \ldots, N$-1). 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 the receiver can be written as:

$$\mathbf{R_p} = \mathbf{X_p}\mathbf{H_p} + \mathbf{N_p} \tag{13}$$

$\mathbf{R_p}$ 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 the pilot-positioned frequency response of the channel. The estimation of channel frequency response in all subcarrier locations for both pilot and data is the 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 more than the equivalent length of the guard interval.

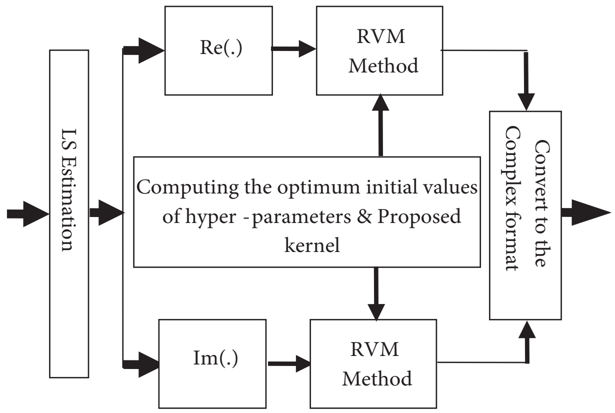

Figure 5. Proposed block diagram.

The initial channel estimation can be achieved by using Eq. (13) as follows [34]:

$$\begin{aligned} \tilde{\mathbf{H}}_{\mathbf{p}} = \mathbf{X}_{\mathbf{p}}^{\mathbf{H}}\mathbf{R}_{\mathbf{p}} &= X_{\mathbf{p}}^{\mathbf{H}}\mathbf{X}_{\mathbf{p}}\mathbf{H}_{\mathbf{p}} + \mathbf{X}_{\mathbf{p}}^{\mathbf{H}}\mathbf{N}_{\mathbf{p}} \\ &= k\mathbf{H}_{\mathbf{p}} + \mathbf{N}_{\mathbf{p}}^{/} \end{aligned} \tag{14}$$

Here, the $(.)^{\mathbf{H}}$ notation indicates the Hermitian-symmetric property. k can control the signal to noise ratio in any pilot location in the frequency domain. If the channel is assumed to be noise-free then $\tilde{\mathbf{H}}_{\mathbf{p}}$ can give the actual frequency response of the channel. In practice, however, $\tilde{\mathbf{H}}_{\mathbf{p}}$ includes the channel that is degraded by additive noises, $\mathbf{N}_{\mathbf{p}}^{/}$. This is simply LS estimation and the following result can be obtained:

$$\mathbf{H}_{\mathbf{LS}} = \frac{1}{k}\mathbf{X}_{\mathbf{p}}^{\mathbf{H}}\mathbf{R}_{\mathbf{p}} = \frac{1}{k}\tilde{\mathbf{H}}_{\mathbf{p}} \tag{15}$$

In the next step, IFFT of Eq. (14) results in the following equation in the time domain:

$$\tilde{\mathbf{h}} = k\mathbf{h} + \mathbf{n}^{/} \tag{16}$$

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

Now the RVM algorithm is applied to estimate $\boldsymbol{h}$ from the observations $\tilde{\mathbf{h}}$ and also reduce noise effects. This is achieved by a sparse Bayesian regression model. It sets a few regression weights to zero and, as a consequence, the noise fitting in $\tilde{\mathbf{h}}$ is canceled. As in Eq. (12), the channel can be approximated by using function f, which is the linear combination of kernel functions, as:

$$f(n) = \sum_i w_i \varphi(n - i) \tag{17}$$

This equation can be viewed as convolution between the regression weight vector and kernel function. This equation can be rewritten in matrix form as Eq. (18):

$$\mathbf{f} = \phi \mathbf{w} \tag{18}$$

Here, $\phi_{ij} = \phi(i-j)$ is the $(i\ ,\ j)$th element of a $\nu\ \times\ \nu$ kernel matrix and $\boldsymbol{w}$ is a column weights vector, which includes ν entries. In most studies, kernel $\phi(n)$ has been considered as a Gaussian function. In this paper, we introduce a new kernel function with low complexity that has more correlative characteristics to PLC channel impulse response and the best fitting is obtained. Various impulse responses used in most references based on the Zimmerman model [39] are shown in Figure 6. It is clear that the suitable basic function as a kernel in our proposed method is more compatible with the triangle model. As a result, we propose the following basic kernel as a shifted triangle function:

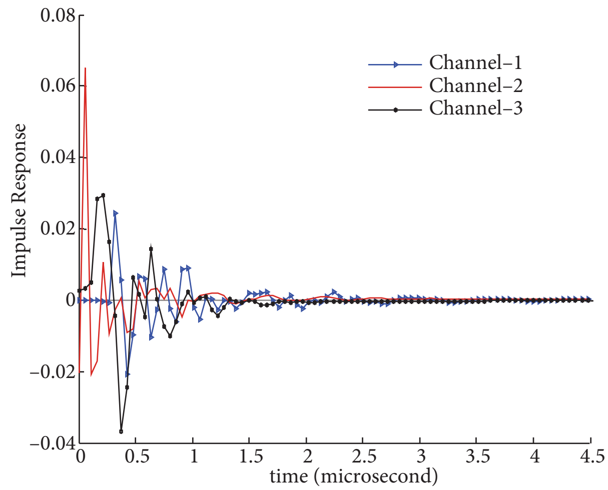

Figure 6. Three types of channel impulse response.

$$\phi(n) = A \times \left| n + \frac{\nu}{4} \right| \tag{19}$$

Here, A is amplitude of the proposed kernel and ν is cyclic prefix size, which is needed to fit as much as possible in the learning phase. In addition to proper fitting of this kernel with channel impulse response, its complexity is significantly low compared to the Gaussian kernel function in the conventional RVM.

Now applying the RVM method to the initial estimation of the channel as in Eq. (16) can give the data in two classes as approximately actual channel and noise, which can be modeled as in the following equation.

$$\tilde{\mathbf{h}} = \mathbf{f} + \mathbf{e} = \phi \mathbf{w} + \mathbf{e} \tag{20}$$

Here, $\boldsymbol{f} = [f_0,\ f_1, \ldots,\ f_\upsilon]^{\mathbf{T}}$ is the approximation function and $\boldsymbol{e} = [e_0,\ e_1, \ldots,\ e_\upsilon]^{\mathbf{T}}$ denotes the error vector in the regression model. The errors are assumed as independent Gaussian random variables, with variance $\sigma^{\mathbf{2}}$ and zero mean, which are identically distributed as follows:

$$p(\mathbf{e}) = \prod_{i=1}^{\upsilon} \mathrm{N}(e_i|0, \sigma^2) \tag{21}$$

If a flexible Gaussian prior over the weights $\boldsymbol{w}$ and Bayesian inference are used, Eq. (21) with an individual hyperparameter for each weight can be written as [42,43]:

$$p(\mathbf{w},\alpha) = \prod_{i=1}^{\upsilon} \mathrm{N}(w_i|0, a_i^{-1}) \tag{22}$$

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

$$p(\mathbf{w}|\tilde{\mathbf{h}},\alpha, \sigma^{\mathbf{2}}) = \mathrm{N}(\mathbf{w}|\mu,\sum) \tag{23}$$

with

$$\sum = (\phi^{\mathrm{T}}\mathrm{B}\phi + \mathrm{A})^{-\mathbf{1}} \tag{24}$$

$$\mu = \sum \phi^{\mathbf{T}}\mathbf{B}\tilde{\mathbf{h}} \tag{25}$$

Here, $\mathbf{B}= \sigma^2\mathbf{I}_\upsilon$, $\mathbf{A}=$ 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 α, σ^2 is obtained:

$$p(\tilde{\mathbf{h}}|\alpha,\sigma^{\mathbf{2}}) = \mathrm{N}(\tilde{\mathbf{h}}|\mathbf{0},(\mathrm{B}^{-\mathbf{1}}+\phi\mathrm{A}^{-\mathbf{1}}\phi^{\mathrm{T}})) \tag{26}$$

The result regression estimation is given by $\boldsymbol{h}_{RVM} = \phi\, mu$ where α and σ can be computed by maximizing the conditional probability, $p(\alpha,\sigma^{\mathbf{2}}|\tilde{\mathbf{h}})$. The maximum likelihood of Eq. (26) is corresponding to the maximum of $p(\alpha,\sigma^{\mathbf{2}}|\tilde{\mathbf{h}})$, when the hyperprior is uniform as assumed [42]. The maximum value of Eq. (26) with respect to α and $\sigma^{\mathbf{2}}$ can be obtained as follows [44]:

$$\alpha_i^{new} = \frac{\gamma_i}{\mu_i^2} \tag{27}$$

and

$$\sigma_{new}^2 = \frac{||\mathbf{t}-\phi\mu||^2}{\upsilon - \sum_i \gamma_i} \tag{28}$$

Here, $mu\ _i$ is the ith weight of the posterior mean given by Eq. (25), and, $\gamma_i = 1 - \alpha_i \sum_{ii}$. $\sum_{ii}$ is the ith diagonal element of the posterior weight covariance matrix based on current α and σ values. In this algorithm, the initial values of the hyperparameters are very important for convergence of the learning process and proper performance. We determine jointly the values of α and σ based on the MMSE criterion. This is similar to the expectation-maximization (EM) algorithm [44] that proceeds by repeating the following steps:

1) Calculate the posterior weight covariance matrix, Σ

2) Find the posterior mean weight, μ

3) Update the hyperparameters, α and σ

4) Calculate the impulse response of estimated channel as $\mathbf{h}_{\mathbf{estimated}}=\phi\mu$

4. Simulation results

To evaluate the performance of our proposed method applied to PLC channels, computer simulations are carried out based on parameters in Table 1. Meanwhile, SNR and SNIR parameters are used in order to compare our proposed algorithm with the conventional RVM and Huang methods. These parameters are defined as follows:

$$SNR = \frac{P_S}{P_N} \tag{29}$$

Here, P_S and P_N are the power of the transmitted signal and AWGN power, respectively, and

$$SNIR = \frac{P_S}{(1-p)P_N + p.P_I} \tag{30}$$

P_I is the impulsive noise power and p is the parameter that can control impulsive and AWGN effects.

Table 1. Simulation parameters.

Parameter	Value
Number of subcarriers, N_c	64, 128, 360, 3072
FFT size, N	256, 512, 4096
Pilot spacing	2–18
Pilot amplitude	1, 0.5
Size of cyclic prefix	64, 512
Baseband modulation	BPSK, 16 QAM
Channel type	PLC (AWGN + impulsive noise)

In order to prove the importance and advantages of our proposed method compared to the Huang method, various comparisons will be shown. In all simulations the PLC channel model is characterized based on parameters in Table 2, which is modeled by the Zimmermann multipath model as in Eq. (1) [39].

Table 2. Parameters of four-path model.

Attenuation parameters		
K=1	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

After proposing a triangle model for the kernel, we consider the effects of initial values of hyperparameters α and σ. Figure 7 shows the MSE criterion with respect to the initial value of these parameters. It is shown that there are at least two local minima and we must choose the values of these parameters to get the optimum values in the steady state. The optimum initial values are chosen based on Figure 7 as $\alpha_i = 8\times 10^{-7}$, $\sigma =$ 0.35. In the second step, we represent the effects of our proposed kernel parameters in the quality of PLC channel estimation. Figure 8 shows the MSE criterion with respect to the kernel amplitude and it is shown that the optimum value is achieved when the amplitude is about 0.08.

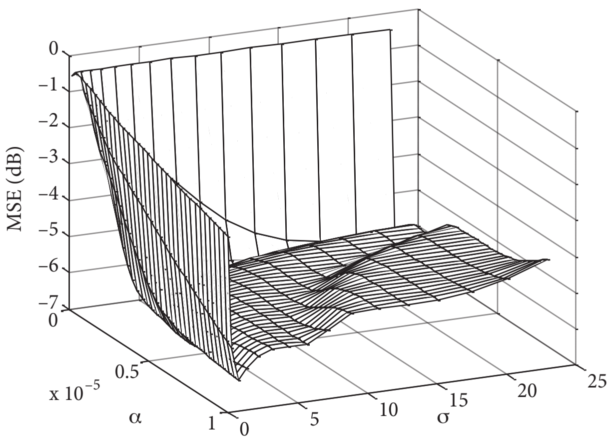

Figure 7. MSE with respect to hyperparameter variation.

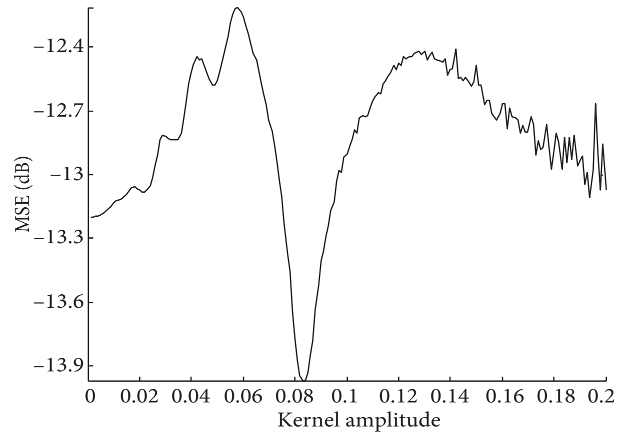

Figure 8. MSE with respect to proposed kernel amplitude, SNR = 15 dB.

Therefore, after applying the obtained optimum values to key parameters in the proposed method, simulation results for channel estimation in both time and frequency domains are shown in Figure 9 with 4% impulsive noise effect and SNR = 0 dB. In this figure, our proposed method is compared with the Huang method along with the actual impulse response of the PLC channel. The proposed method shows good results compared to the Huang method.

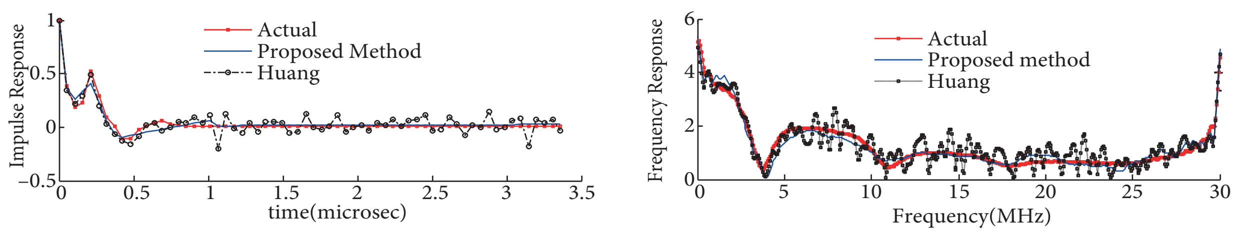

Figure 9. Impulse response curves with SNR = 0 dB, impulse noise effect = 4%.

For further evaluation of our proposed method, the MSE and BER parameters are plotted in Figures 10 and 11, respectively. Variation of SNIR is –0.5 dB to 17 dB and BPSK modulation is used in these simulations. In these figures, the results of the Huang method are also shown for comparison. MSE curves show about 5 dB enhancements in our proposed method in comparison with the Huang method for various SNIRs. BER curves also confirm this. Figure 12 shows MSE improvement versus pilot space effects in the proposed algorithm compared to the Huang method. As is clear, pilot amplitude plays an important role in local signal to noise ratio management and channel estimation. Therefore, in order to represent more differences between our proposed method and the Huang method, the MSE parameter is investigated in the presence of impulsive noise effects and pilot amplitude variations. The obtained results for pilot amplitudes of 0.5 and 1 are seen in Figure 13.

Finally, the robustness of our proposed method against the Huang method is shown in Figures 14–16. For instance, in Figure 14, when the effect of impulsive noise is increased, MSE improvement of about 4 dB for 60% impulsive noise effect is achieved in our proposed method compared to the Huang method. Figure 15 shows the MSE comparison of our proposed method with the Huang and improved complex RVM approaches when the subcarrier numbers and cyclic prefix size are selected according to PLC standards as P1901, 3072, and 512, respectively.

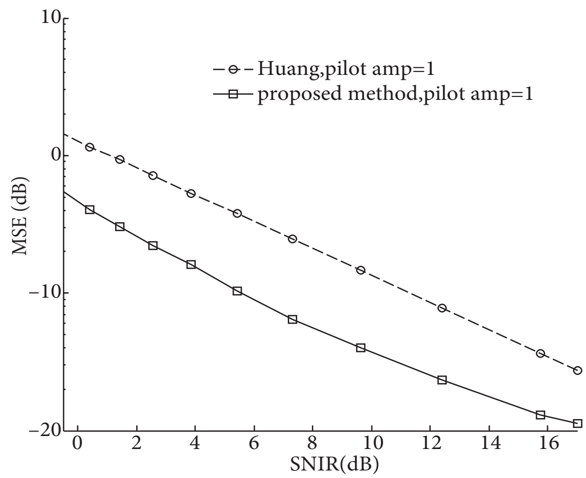

Figure 10. MSE comparison, BPSK, N = 512, Nc = 360, CP = 64, pilot space = 4.

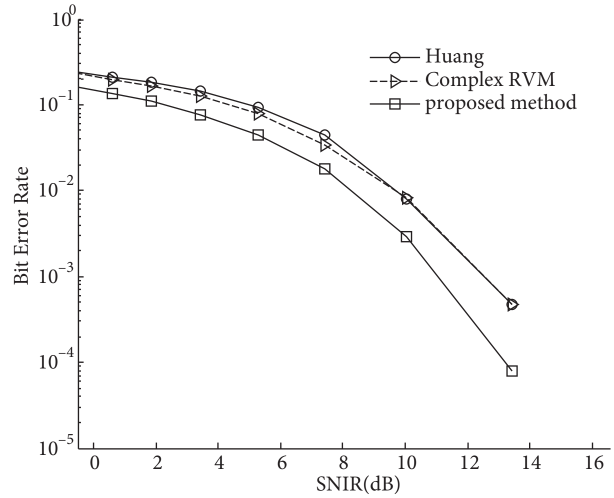

Figure 11. BER results, BPSK, N = 512, Nc = 60, CP = 64, pilot space = 4.

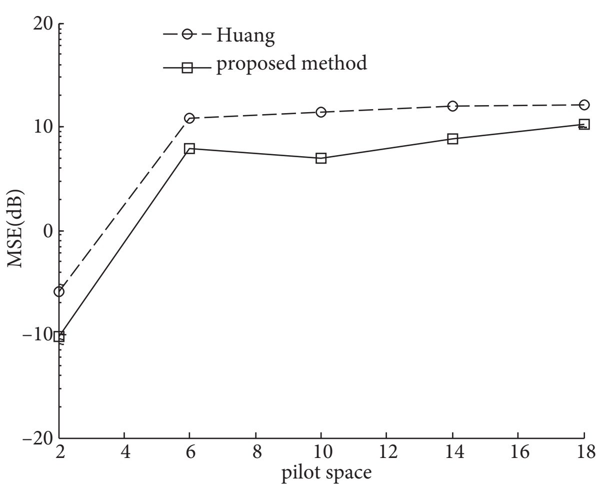

Figure 12. MSE versus pilot space effects.

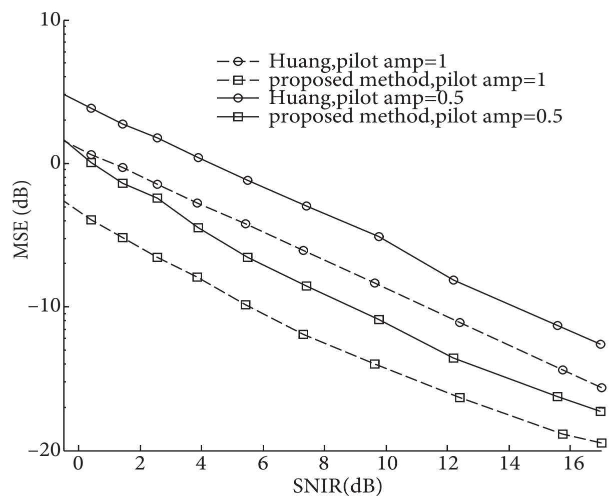

Figure 13. Pilot amplitude effects, CP = 64, N = 512, Nc = 360, BPSK, pilot space = 4.

At the end of the simulation results, the MSE criteria of the three mentioned techniques for 16QAM modulation are shown in Figure 16 to prove the robustness of the proposed method.

5. Conclusion

In this article, a new kernel function was proposed along with computing of optimum values for hyperparameters. Complex-valued analysis based on a RVM was used to estimate the PLC channel. This proposed kernel caused good enhancement in the obtained channel estimation results. The variations of pilot spaces and pilot amplitudes were demonstrated in our proposed algorithm. It was shown that MSE and BER criteria were enhanced in any conditions. In addition, the influence of impulsive noise increasing on quality of channel estimation in our proposed method was compared with the recently reported Huang method and improved conventional RVM with Gaussian kernel function. The robustness of the proposed method against impulsive noise effects was completely proved.

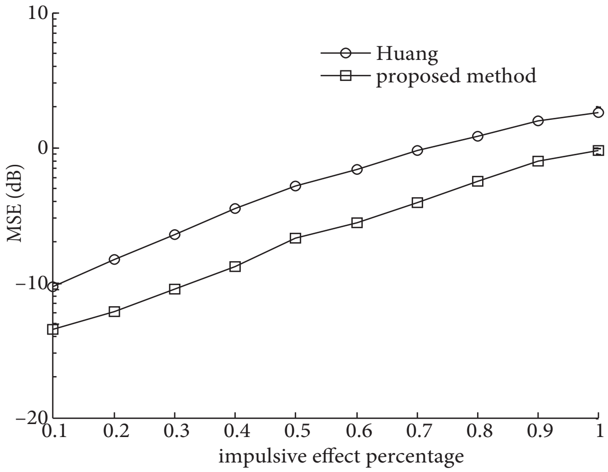

Figure 14. Impulsive noise effects, BPSK, N = 256, Nc = 64, CP = 64, pilot space = 4.

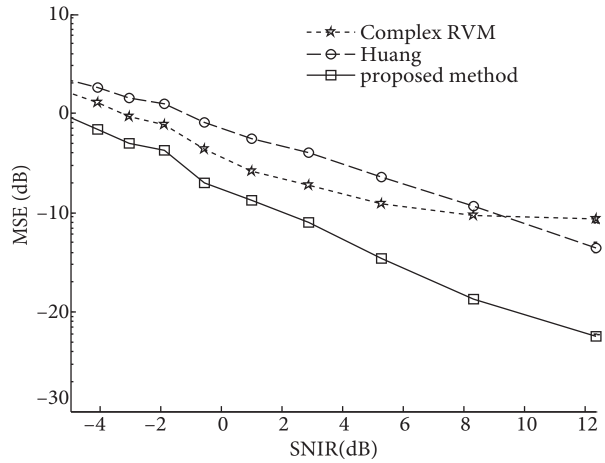

Figure 15. MSE comparison, BPSK, N = 4096, Nc = 3072, CP = 512, pilot space = 4.

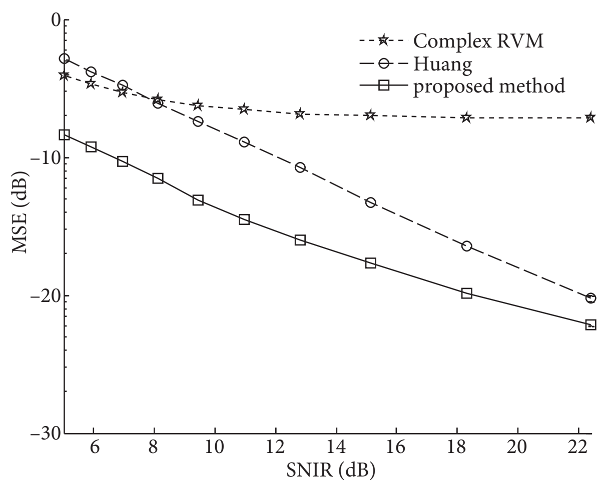

Figure 16. MSE comparison, 16QAM, N = 256, Nc = 128, CP = 64, pilot space = 4.

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