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A cooperative modulation recognition: New paradigm for power line networks in smart grid

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ABSTRACT

Power Line communication (PLC) is an attractive approach to provide information transfer services for future smart grids. However, since various modulations are adopted, it is a great challenge to add new nodes to collect the data from the devices or sensors in in-home PLC networks. In this paper, we propose an approach to automatically access to the PLC network by identifying the modulation of signals. To improve the correct recognition rate on identification of modulations, we propose a multiple input and multiple output (MIMO) based cooperative modulation identification scheme. After receiving the recognition results from accessing nodes, the central server makes the comprehensive and accurate recognition decision on the modulation of the PLC network. Furthermore, the fourth-order cumulants for multiple users are adopted as the feature for this modulation classifier. With the feature, we propose an improved modulation classification algorithm based on the maximum likelihood. Simulations show that a high detection rate and low false positive rate can be achieved as we employ the cooperative modulation identifying scheme and the improved recognition algorithm.

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1. Introduction

Increasing interest in smart home automation systems, in-home networks, or multimedia systems requires a new network paradigm to connect all indoor communication devices, such as an indoor local-area network (LAN) [1]. This requirement has driven the use of low-voltage power lines as a high-speed communication channel because the power-line grid over a house is a better and more widely distributed pre-deployed network than any other communication networks in the home [2–4]. Hence, the power line communication (PLC) is an appropriate network technology for in-home applications when compared to other communication methods.

In order to achieve high spectral efficiency, differential modulations are employed in the PLC networks. The differential phase shift keying (DPSK), as in [5], is an effective approach for PLC, where the constellation has one magnitude and different phase changes. In order to improve its efficiency, researchers often increase the points in the constellation. However, the performance of this modulation is degraded as its points exceed sixteen due to the

close points location. Thus, authors in [6] prove the constellation with 8PSK is most effective. Additionally, authors of [7] address the usage of M-QAM modulation for PLC systems under impulsive noise. By adopting M-QAM, PLC systems with Orthogonal Frequency Division Multiplexing (OFDM) scheme can achieve a better performance on bit error rate than those of systems without OFDM. Unfortunately, various modulations used in PLC networks bring a great challenge to add new sensors into the system, since the added sensors cannot communicate with original nodes in PLC network – this limits the scope of PLC networks.

For the sake of providing automatic access for sensors, the practical scheme for the PLC network is designed as a cognitive sensor network. With this approach, sensors can add in PLC networks as nodes by identifying the adopting demodulation and estimating demodulation parameter [8]. Hence, in these added sensors, we need to install a modulation recognizing component. Generally, the modulation recognizing component is composed by two subsystems, feature extraction subsystem and pattern recognizing subsystem. The feature extraction subsystem extracts the key features from received signals [9]. According to [10], the most appropriate feature for modulation recognition are higher-order statistics (HOS), including cumulants and moments. To improve the performance of a classifier, the combination of second and fourth order cyclic cumulants (CC) magnitudes has been proposed

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in [11]. Similarly, the higher-order up to eighth-order CC magnitudes is adopted in [12] and *n*th-order warped CC magnitudes are utilized in [13] in order to improve the recognizing rate. Validating the results in [14] shows cumulants are preferred as the features due to their favorable properties. However, when adopting cumulants with order higher than four, longer time is needed to train data and process recognition.

The second subsystem is the pattern recognizer, which processes features and determines the modulation of signals according to pre-designed decision rules. There are two classes of algorithms that can be used to identify modulations, the likelihood-based (LB) [15,16] and feature-based (FB) [17] methods. The former is based on the likelihood function of received signals and its decision is made by comparing the likelihood ratio against a threshold. A solution offered by the LB algorithm is optimal in the Bayesian sense, which minimizes the probability of false classification [18]. Unfortunately, the optimal solution often suffers from computational complexity, which in many cases of interest naturally gives rise to suboptimal classifiers. However, the FB method can identify the modulation with a different scheme [19]. First, it extracts several features of various given modulations with a prepared training data set. By capturing signals, the modulation identification algorithm can then calculate values for the features of the modulation used in the specified network. At last, the algorithm makes a choice on the modulation by comparing the calculated results with the training ones. Hence, a FB method may not be optimal. Nonetheless, according to [15,20], it is usually simple to be implemented, with near-optimal performance, if designed properly.

Automatic recognition can identify the modulated signal within specific frequency range, which makes the users change corresponding mechanism of transmission and reception according to the external spectral environment, and thus improves the spectrum utilization [21]. However, the existing ways of modulation modes recognition mainly focus on monitoring and identifying the single signal whereas little attention was paid to study the recognition of multiuser signal modulation mode. In order to solve the aforementioned problem, the technology of recognizing multiuser signal modulation mode is automatically developed in [22]. However, modulation identification for a PLC system is a challenging task, especially in a non-cooperative environment, where in addition to multi-path propagation, frequency-selectivity and no prior knowledge of the incoming signal is available [23].

In this paper, we propose to use the modulation identification to help sensors to automatically access to the PLC in-home networks. To the best of the authors knowledge, our work is the first of its kind to construct a PLC in-home network with MIMO to aid the cooperative modulation recognition. Compared to many other modulation identification method, we build fourth order cumulants of multiple nodes as the feature, with which we can identify modulations with received recognition results from several accessed nodes. In particular, we propose the following five-fold contributions:

- We design a model for PLC in-home networks, where sensors can access the network as new nodes via PLC sockets. This scheme provides a new way to collect information from PLC sensors network.
- We propose a cooperative modulation identification method in PLC in-home network based on PLC MIMO channel, where several wires are used for communication. The central server can simultaneously receive the modulation recognition information from accessing nodes.
- We adopt the fourth-order cumulants of multiple nodes as the feature for the modulation classifier, which can recognize modulation of signals by collecting samples from several accessing nodes.
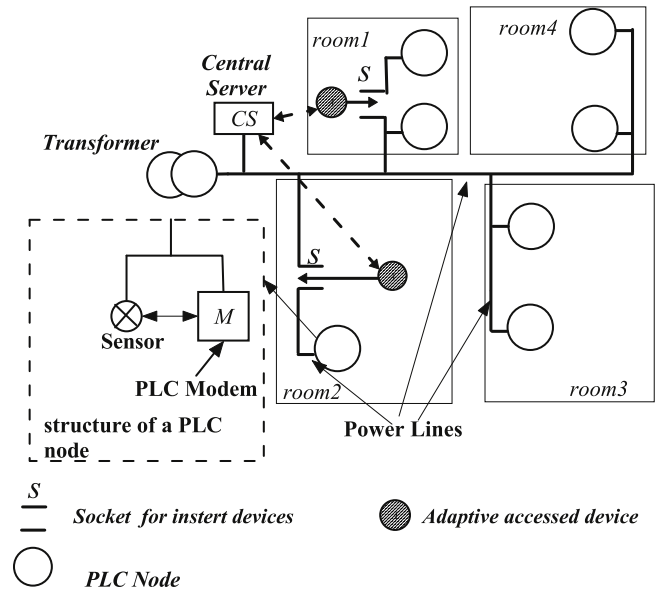

Fig. 1. A typical structure of an in-home PLC network by using the cooperative modulation recognition. The adaptively accessed sensor is the new adding node which need to identify modulation of the system, the central server *CS* is the central node which can receive modulation identification results from multiple ASs, and PLC FNs can be composed by a sensor and a PLC modem.

- We design an improved modulation recognition algorithm based on maximum likelihood by introducing the weighting factor.
- Simulations show that a higher recognition rate and a lower false positive rate are achieved when adopting the proposed cooperative modulation recognition algorithm.

The remainder of this paper are organized as follows. Section 2 describes the cooperative modulation identification scheme for the PLC in-home network systems. Section 3 formulates the feature extraction method for the modulation classifier. Then, Section 4 presents the improved modulation classification algorithm. In Section 5, we present numerical results to demonstrate the performance of proposed algorithms. Finally, Section 6 concludes the paper.

2. System model and assumptions

In the PLC network system, as shown in Fig. 1, the PLC flexed nodes (FN) are installed at the loads, such as the meters or electrical lights. The automatically accessed sensor (AS) is a new node added into PLC network, which needs to identify the modulation used by FN to transmit signals. These ASes sent their results about the modulation identification to a central server (CS). That is, by obtained the feature of signals, the ASes can estimate the modulation primitively and send the estimated results to the CS. According to these received features from ASs, CS makes the final decision on the modulation used in the system. At last, CS feeds back the final identification results to ASs.

Since the CS can collect primitive modulation identification results from independent ASes, it can make a comprehensive judgment on the modulation. In this way, the cooperative modulation recognition approach can improve the performance of correct recognition rate and false positives rate i.e., a modulation of the signals being detected as one when it was not. However, in our model, the CS is required to receive signals from several ASes quickly, so that the training and recognizing process would not be
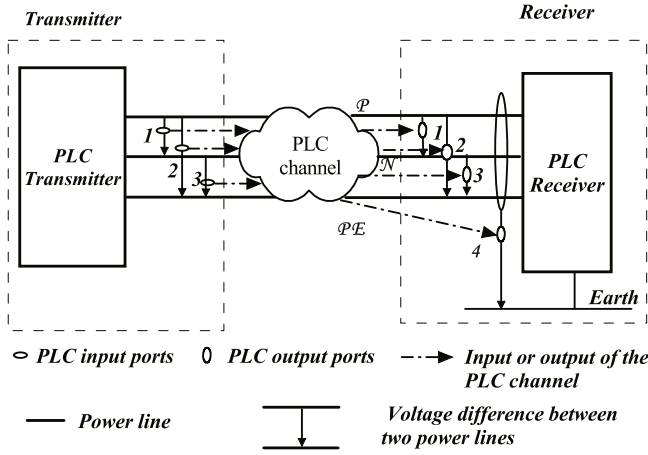
Fig. 2. The PLC channel for a 3-wire installation, where signals are transmitted and received differentially between pairs of wires. There are three input (or transmission) ports: $\mathcal{N} - \mathcal{PE}$, $\mathcal{P} - \mathcal{N}$, and $\mathcal{P} - \mathcal{PE}$, and four output (or receiving) ports $\mathcal{N} - \mathcal{PE}$, $\mathcal{P} - \mathcal{N}$, $\mathcal{P} - \mathcal{PE}$, and sum$(\mathcal{P}, \mathcal{PE}, \mathcal{N})$ − earth.

delayed at CS. Thus, we design a PLC-MIMO structure for the in-home network to implement simultaneous transmission from ASs to the CS, shown as Fig. 2.

The PLC-MIMO system is constructed by combining the power line structure with the typical MIMO model. According to the structure of three-wire power line, the power line is composed of a phase ($\mathcal{P}$), a neutral ($\mathcal{N}$), and a protective earth ($\mathcal{PE}$) [24]. Signals are transmitted as the voltage difference between two power wires, and thus there are three kinds of transmission ports, i.e., $\mathcal{P}$ to $\mathcal{N}$, $\mathcal{P}$ to $\mathcal{PE}$, and $\mathcal{N}$ to $\mathcal{PE}$. Generally, this voltage difference between two power wires can be called as port. However, only two ports can be exploited as communication ports for the reason that the sum of the voltage differences between the three wires is zero, according to Kirchhoff's law in the circuit [25].

Generally, the PLC-MIMO channel with N transmitting ports and M receiving ports has the channel matrix H, described by

$$\mathbf{H} = \begin{bmatrix} h_{1,1} & \cdots & h_{1,n} & \cdots & h_{1,N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ h_{m,1} & \cdots & h_{m,n} & \cdots & h_{2,N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ h_{M,1} & \cdots & h_{M,n} & \cdots & h_{M,N} \end{bmatrix}, \tag{1}$$

where $h_{m,n}$ is the complex channel transfer function coefficient from the nth ($n = 1, \ldots, N$) transmitting port to the mth ($m = 1, \ldots, M$) receiving port. As in [26], the time domain expression of $h_{m,n}$ can be given by

$$h_{m,n}(t) = \sum_{i=1}^{\eta_{m,n}} g_{m,n,i} A_{m,n,i}(f, \ell_{m,n,i}) \cdot e^{-j\phi_i} \delta(t - \tau_{m,n,i}), \tag{2}$$

where $\eta_{m,n}$ is the number of propagation paths from the nth transmitting port to the mth receiving port, f is the natural frequency, $\ell_{m,n,i}$ is the power line length from the nth transmission port to the mth reception port over the ith propagation path, $\tau_{m,n,i}$ is the delay related with $\ell_{m,n,i}$, $g_{m,n,i}$ is the weighting factor comprised of the reflection and transmission factors along a propagation path, $\delta(\cdot)$ is the impulse function, and $A_{m,n}(f, \ell_{m,n,i})$ is the attenuation that increases with the frequency f. With the assumption that the signals are transmitted at the same speed over each path, $A_{m,n}(f, \ell_{m,n,i})$ can be approximated as

$$A_{m,n}(f, \ell_{m,n,i}) = e^{-(a_0 + a_1 f^q) \cdot \ell_{m,n,i}}, \tag{3}$$

where the constants a_0, a_1, and q are obtained by measuring the frequency response of the system.

For the mth reception port, where $1 \le m \le M$, the received signal y_m can be expressed as

$$y_m = \sum_{n=1}^{N} h_{m,n} x_n + z_m, \tag{4}$$

where x_n is the signal transmitted from the nth transmitting port, and z_m is the receiving noise at the mth receiving port.

According to (1) and (4), we can describe the PLC-MIMO channel model as

$$\mathbf{y} = \mathbf{H}x + \mathbf{z}, \tag{5}$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_N]^T$ is the transmitting signal vector, $\mathbf{y} = [y_1, y_2, \ldots, y_M]^T$ is the receiving signal vector, and $\mathbf{z} = [z_1, z_2, \ldots, z_M]^T$ is the noise vector.

We can pre-process the obtained signals and a baseband sequence composed of samples acquired from the signal. If the jth AS sends the signal x to the ith port of CS with different path, it can be written as

$$y_i = h_{i,j} x(0) + h_{i,j} x(1) \omega^{-1} + \cdots + h_{i,j} x(L) \omega^{-L}, \tag{6}$$

where L is the sampling time moment number, ω^{-1} is the unit delay operator.

In this system, we have the following assumptions on the PLC MIMO channels:

- The mean of $x(l)$ is zero, and the transmitting signals of different users are independent

$$\mathbb{E}\left[x(l) * x^*(l + \tau)\right] = \begin{cases} I_l, & \tau = 0 \\ O, & \tau \ne 0, \end{cases} \tag{7}$$

where I and O are the unit matrix and the zero matrix respectively.

- $z(l)$ is an additive white Gaussian noise with zero mean and variance of σ_z^2.

$$\mathbb{E}\left[z(l) * z^*(l + \tau)\right] = \begin{cases} \sigma_z^2 I_m, & \tau = 0 \\ O, & \tau \ne 0. \end{cases} \tag{8}$$

3. Characteristics specification

Currently, among the methods of modulation recognition, classifier with high order cumulant is an effective method to identify modulation for signals. In this paper, we introduce a cooperative modulation recognition approach, which will predictively improve the performance of the classifier.

3.1. Fourth order cumulant

In this subsection, we can preprocess the obtained signals and a baseband sequence composed of samples $\{x(l)\}_{l=1}^{L}$ acquired from the signal. Then, our aim is to identify the constellation of samples sequence $\{x(l)\}$ drawn from a known constellation collection. That is, given L samples, $\{x(l)\}$, we wish to decide whether the signal is drawn from one of the known constellations.

To identify the modulation, we use the fourth order cumulants. To present the definition on the fourth order cumulants, we need first to feed the second order cumulants for a stochastic process $x(l)$ in the following two ways

$$C_{20} = \mathbb{E}\left(x^2(l)\right), \tag{9}$$

$$C_{21} = \mathbb{E}\left(|x(l)|^2\right), \tag{10}$$

Second, we present three definitions of the fourth order cumulants in three ways as follows

$$C_{40} = \mathbb{C}\left(x\left(l\right), x\left(l\right), x\left(l\right), x\left(l\right)\right),\tag{11}$$

$$C_{41} = \mathbb{C}\left(x\left(l\right), x\left(l\right), x\left(l\right), x^*\left(l\right)\right),\tag{12}$$

and

$$C_{42} = \mathbb{C}\left(x\left(l\right), x\left(l\right), x^*\left(l\right), x^*\left(l\right)\right),\tag{13}$$

where the function $\mathbb{C}(\cdot)$ is a fourth order cumulant. Given four stochastic variables w, x, y and z with the mean zero, $\mathbb{C}(\cdot)$ can be defined as

$$\begin{aligned}\mathbb{C}\left(w, x, y, z\right) &= \mathbb{E}\left(wxyz\right) - \mathbb{E}\left(wx\right)\mathbb{E}\left(yz\right)\\&\quad - \mathbb{E}\left(wy\right)\mathbb{E}\left(xz\right) - \mathbb{E}\left(wz\right)\mathbb{E}\left(xy\right).\end{aligned}\tag{14}$$

In following, we demonstrate how to use the fourth order cumulant to estimate. From (11) and (14), we have

$$\hat{C}_{40} = \frac{1}{L}\sum_{n=1}^{L}x^4\left(l\right) - 3\hat{C}_{20}^2,\tag{15}$$

where $\hat{C}_{20}^2$ is the estimated second order cumulant of $x\left(l\right)$, given by

$$\hat{C}_{20} = \frac{1}{L}\sum_{l=1}^{L}x^2\left(l\right).\tag{16}$$

Similarly, according to (11), (12) and (14), another two fourth order cumulants of $x(n)$ can be estimated by

$$\hat{C}_{41} = \frac{1}{L}\sum_{l=1}^{L}x^3\left(l\right)x^*\left(l\right) - 3\hat{C}_{20}\hat{C}_{21},\tag{17}$$

and

$$\hat{C}_{42} = \frac{1}{L}\sum_{l=1}^{L}\left|x\left(l\right)\right|^4 - \left|\hat{C}_{20}\right|^2 - 2\hat{C}_{21}^2,\tag{18}$$

where $\hat{C}_{21}^2$ is the estimated second order cumulant of $x\left(l\right)$, given by

$$\hat{C}_{21} = \frac{1}{L}\sum_{l=1}^{L}\left|x\left(l\right)\right|^2.\tag{19}$$

Without losing the generality, if we normalize the power of the signals, the standardized fourth order cumulant for the signal with different modulation modes can be expressed as

$$\tilde{C}_{4k} = \frac{\hat{C}_{4k}}{\hat{C}_{21}^2}, k = 0, 1, 2.\tag{20}$$

As there is one user transmits signal with PLC channel, the received signal can be expressed as

$$y = \sum_{k=0}^{L-1}h_{i,j}x\left(l - k\right) + z\left(l\right),\tag{21}$$

where y is the received signal, $x\left(l\right)$ is the transmitted signal, $z\left(l\right)$ is the noise in the PLC channel, and $h\left(l\right)$ is the mitigation coefficient in the corresponding path.

In this case, the fourth order cumulant and second order cumulant of the received signal for the PLC channel can be formulated as

$$C_{40,y} = \sum_{k=0}^{L-1}\left|h_{i,j}\right|^4 C_{40},\tag{22}$$

and

$$C_{21,y} = \sum_{k=0}^{L-1}\left|h_{i,j}\right|^2 C_{21} + \sigma_\omega^2.\tag{23}$$

As given in (20), then, we derive the standardized fourth order cumulant for the received signal

$$\tilde{C}_{40,y} = \frac{C_{40,y}}{\left(C_{21,y} - \sigma_\omega^2\right)^2}.\tag{24}$$

3.2. Cumulant for multiple users

In this subsection, we consider the fourth order cumulant in multiple users scenarios. As the multiple users transmit signals to CS, the receiving signals at the ith port is given as

$$y_i = h_{1,i}x_1\left(l\right) + h_{2,i}x_2\left(l\right) + \cdots + h_{M,i}x_l\left(l\right) + z_i\left(l\right),\tag{25}$$

According to the (20) and (22), the $\hat{C}_{4k,y_i}$, $(k = 0, 1, 2)$ of $x_j\left(l\right)$ can be expressed as

$$\hat{C}_{4k,y_i} = \mu_{1,i}\hat{C}_{4k,x_1} + \cdots + \mu_{M,i}\hat{C}_{4k,x_M},\tag{26}$$

where $k = 0, 1, 2$, and μ can be given as

$$\mu_{m,i} = \sum_{m=1}^{M}h_{m,i}^4,\tag{27}$$

Similarly, $\hat{C}_{21,y_i}$ of the received signal at the ith port can be expressed as

$$\hat{C}_{21,y_i} = h_{1,i}^2\hat{C}_{21,x_1} + \cdots + h_{M,i}^2\hat{C}_{21,x_M} + \sigma_z^2 = \Delta_i + \sigma_z^2,\tag{28}$$

Since $\hat{C}_{21,x_j} = 1$, $(j = 1, 2, \ldots, M)$ for the random transmitting signal $x_j\left(l\right)$, we can derive

$$\Delta_i = h_{1,i}^2 + \cdots + h_{M,i}^2,\tag{29}$$

With (20) and (24), it follows that

$$\tilde{C}_{4k,y_i} = \frac{\hat{C}_{4k,y_i}}{\left(\hat{C}_{21,y_i} - \sigma_w^2\right)^2} = \sum_{i=0}^{M}\frac{\mu_{m,i}}{\Delta_i^2}\hat{C}_{4k,x_m}, k = 0, 1, 2.\tag{30}$$

We then transform (30) into a vector form, given as

$$\begin{pmatrix}\hat{C}_{4k,y_1}\\\vdots\\\hat{C}_{4k,y_M}\end{pmatrix} = \begin{pmatrix}\frac{\mu_{1,1}}{\Delta_1^2} & \cdots & \frac{\mu_{1,N}}{\Delta_1^2}\\\vdots & \ddots & \vdots\\\frac{\mu_{M,1}}{\Delta_M^2} & \cdots & \frac{\mu_{N,M}}{\Delta_M^2}\end{pmatrix}^T\begin{pmatrix}\hat{C}_{4k,x_1}\\\vdots\\\hat{C}_{4k,x_M}\end{pmatrix}.\tag{31}$$

We further simplify (31) as

$$\vec{C}_{4k,y} = \mathbf{U}\vec{C}_{4k,x}, k = 0, 1, 2,\tag{32}$$

where the matrix $\mathbf{U}$ is given as

$$\begin{pmatrix}\frac{\mu_{1,1}}{\Delta_1^2} & \cdots & \frac{\mu_{1,N}}{\Delta_1^2}\\\vdots & \ddots & \vdots\\\frac{\mu_{1,M}}{\Delta_M^2} & \cdots & \frac{\mu_{N,M}}{\Delta_M^2}\end{pmatrix}^T.\tag{33}$$

Since signals are received by different ASs, these input signals can be assumed to be independent. Thus, according to (1), $\mathbf{H}$ is full rank. Therefore, according to (28) and (29), $\mathbf{U}$ is full rank. As a result, the solution of (32) can be expressed as

$$\vec{C}_{4k,x} = \left(\mathbf{U}^H\mathbf{U}\right)^{-1}\vec{C}_{4k,y}.\tag{34}$$

Note that, the channel matrix $\mathbf{H}$ in $\mathbf{U}$ is usually unknown to ASes. Then, we calculate the matrix $\mathbf{U}$ in order to estimate the channel matrix $\mathbf{H}$.
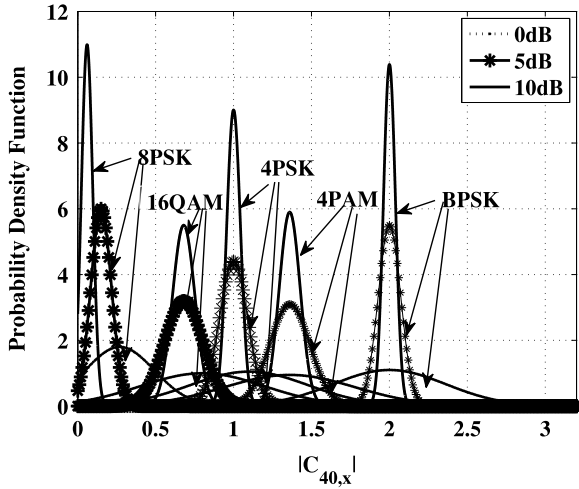
Fig. 3. Comparison of the PDF of the channel gain for different modulations as we use $|C_{40,x}|$ to estimate the signals with different SNR.
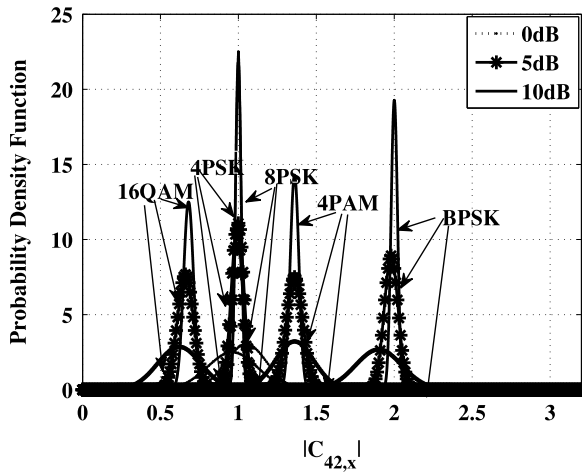

Fig. 4. Comparison of the PDF of the channel gain for different modulations, where $|C_{42,x}|$ is used to estimate the signals with different SNR.

In following, we estimate the **H** by calculating PDF of different modulations of transmitting signals using simulation settings. Since the absolute value $\left|\hat{C}_{4k,y}\right|$ indicates the PDF of modulations, we need to estimate $\left|\hat{C}_{4k,y}\right|$ by calculating the absolute value $\left|\hat{C}_{4k,x}\right|$ with (30). For simplicity, we denote $\left|\hat{C}_{40,x}\right|$ and $\left|\hat{C}_{42,x}\right|$ as M_{C40_x} and M_{C42_x}. Then, we calculate M_{C40_x} and M_{C42_x} of signals modulated by BPSK, 4PAM, 4PSK, 8PSK, and 16QAM with SNR from $-50-\!-20$ dB.

The estimated results PDF of the channel gain for different modulations against M_{C40_x} and M_{C42_x} are shown in Figs. 3 and 4. As shown in the two figures, when the SNR is 5 dB and 10 dB, the simulation results of M_{C40_x} and M_{C42_x} are approximately equal to the computational value as listed in Table I of [10]. Simulation results of Figs. 3 and 4 also demonstrate that M_{C40_x} and M_{C42_x} of the transmitting signals can be used to detect the modulations effectively.

Fig. 5 demonstrates the plots of joint PDF for the channel gain of multi-users as we use M_{C40_x} and M_{C42_x} to estimate the signals with different SNR. We observe that the scheme of multi-user cooperative modulation identification is better than that of the single receiver users, especially when the modulation scheme of 4PSK and 8PSK are adopted. The reason is that the multiuser
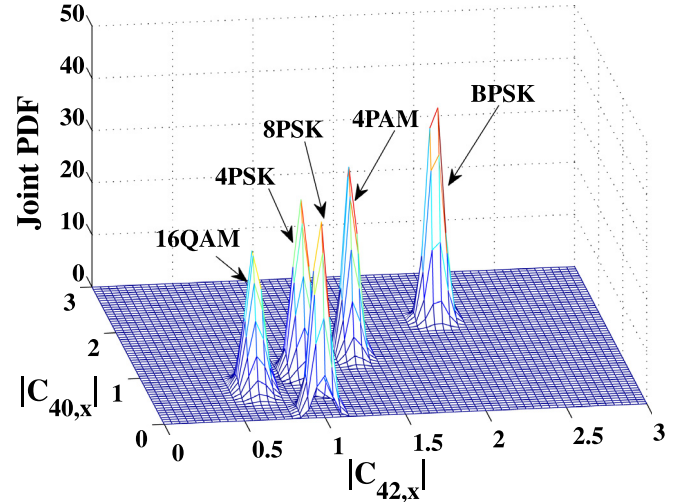

Fig. 5. Comparison of the joint PDF of different modulations as we use $|C_{40,x}|$ and $|C_{42,x}|$ to estimate the signals with different SNR.

cooperative modulation can combine all the identification data from several ASes.

4. Modulation identification

In this section, we adopt a centralized modulation recognition algorithm based on joint probability distribution of fourth order cumulant M_{C40_x} and M_{C42_x}. Each AS receives signals from FNs and then estimates the M_{C40_x} and M_{C42_x} of transmitting signals. Then these fourth order cumulants of ASs are uploaded to the CS, which form a fourth-order cumulant vector. With this vector, CS make the final judgment on modulation.

4.1. Decision rule

As shown in Fig. 1, we assume that there are M ASes $S = S_1, S_2, \ldots, S_M$, where each AS receives signals from FNs. The channel between AS and FN can be modeled as a PLC-MIMO channel. Suppose there are Θ modulations, $\mathbb{M} = [\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_\Theta]$. In addition, the energy of signals are assumed as one.

Each AS can calculate SNR and estimate the M_{C40_x} and M_{C42_x} of receiving signals. Then, ASes upload their $\left(M_{C40_x}, M_{C42_x}, \gamma\right)$ to the CS. The obtained fourth order cumulants vector is given as

$$\mathbf{C} = \left(\left(M_{C40_{x_1}}, M_{C42_{x_1}} \right), \left(M_{C40_{x_2}}, M_{C42_{x_2}} \right), \right.$$
$$\left. \cdots, \left(M_{C40_{x_N}}, M_{C42_{x_M}} \right) \right) \tag{35}$$

where $M_{C40_{x_i}}$ and $M_{C42_{x_i}}$ are the absolute value of the four order cumulant of ith AS, sent to the CS.

As given in **C** in (35), CS can make the decision on the modulation $D\,(D \in \mathbb{M})$ of signals with their SNR vector $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_M)$. Since the computation of the four order vectors depend on the calculation of M_{C40_x} and M_{C42_x} at CS, which has an intensive computational ability, the system can work efficiently. Additionally, the transmission of the four order cumulants in ASes does not require a high bandwidth.

By using the Bayes' formula on probability theory, we obtain the conditional probability, written as

$$\Pr\left(D = \mathcal{M}_\varsigma \,|(M_{C40}, M_{C42}, \gamma)\right)$$
$$= \frac{\Pr\left((M_{C40}, M_{C42}, \gamma) \,|D = \mathcal{M}_\varsigma\right) \Pr\left(D = \mathcal{M}_\varsigma\right)}{\sum_{i=1}^{\Theta} \Pr\left((M_{C40}, M_{C42}, \gamma) \,|D = \mathcal{M}_l\right) \Pr\left(D = \mathcal{M}_l\right)}, \tag{36}$$

where $\Pr\left(D = M_\varsigma\right)$ is the prior probability of the ς ($1 \le \varsigma \le \Theta$) modulation M_ς. By assuming probabilities of the occurrences of all modulation are same, we can obtain

$$\Pr\left(D = \mathcal{M}_\varsigma\right) = \frac{1}{\Theta}. \tag{37}$$

Since each AS can independently estimate the cumulative value, we can derive the conditional probability of M_{C40_x} and M_{C42_x} under the condition of modulation mode $D = M_m$ and γ, expressed as

$$\Pr\left((M_{C40}, M_{C42}, \gamma)\,\big|\,D = \mathcal{M}_\varsigma\right)$$
$$= \prod_{i=1}^{N} \Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}, \gamma_i\right)\big|\,D = \mathcal{M}_\varsigma\right), \tag{38}$$

where M_{C40_i} and M_{C42_i} is the theoretical value of the absolute value of standardized fourth order cumulant of the modulation signal at the ith AS.

In (38), $\Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}, \gamma_i\right)|D = \mathcal{M}_\varsigma\right)$ is the probability of cumulative value estimated by the single AS, which thus can be given as

$$\Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}, \gamma_i\right)\big|\,D = \mathcal{M}_\varsigma\right)$$
$$= \frac{\Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}\right)|\gamma_i, D = \mathcal{M}_\varsigma\right)}{\sum_{l=1}^{\Theta} \Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}\right)|\gamma_i, D = \mathcal{M}_l\right)}. \tag{39}$$

With the maximum likelihood method, we set up the decision rule as follow

$$D = \arg\max_\varsigma \left\{\Pr\left((M_{C40}, M_{C42}, \gamma)\,\big|\,D = \mathcal{M}_\varsigma\right)\right\}, \tag{40}$$

Substituting the (39) and (40) in (38), the final decision can be expressed as

$$D = \arg\max_\varsigma \left\{\Pr\left((M_{C40}, M_{C42}, \gamma)\,\big|\,D = \mathcal{M}_\varsigma\right)\right\}$$
$$= \arg\max_\varsigma \left\{\prod_{i=1}^{M} \frac{\Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}\right)|\gamma_i, D = \mathcal{M}_\varsigma\right)}{\sum_{l=1}^{\Theta} \Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}\right)|\gamma_i, D = \mathcal{M}_l\right)}\right\}. \tag{41}$$

4.2. Identification algorithm

In this subsection, we develop an improved method to identify modulations of signals based on maximum likelihood ratio with the weighting factors. They are designed according to M_{C40} and M_{C42}, which can strengthen the character to improve the performance of the identification algorithm. The modulation identification algorithm is given as Algorithm 1.

Algorithm 1 The Weights Based Maximum Likelihood Modulation Identification Algorithm (WMLMIA)

Require: Set $P = 1, Q = 0, D = 0$.
1: **while** $m = 1$ to Θ **do**
2:    **for** $i = 1; i < M; i++$ **do**
3:       Compute $w_{i,\varsigma}$ with (42);
4:       Compute $P_{i|\varsigma}$ with (39);
5:       Determine $P = P * (w_{i,\varsigma} * P_{i|\varsigma})$;
6:    **end for**
7:    **if** $P > Q$ **then**
8:       $Q = P, D = \mathcal{M}_\varsigma$;
9:    **end if**
10: **end while**

At the line 3 of the Algorithm 1, $w_{i,\varsigma}(\varsigma = 1, 2, \ldots, \Theta)$ is the weighting factor, designed according to M_{C40_x} and M_{C42_x}. The factor

Table 1
Simulation parameters setting.

Parameter name	Value
Path parameter g_i	-0.15
Path number parameter η	3
Fading parameter a_0	0
Fading parameter a_1	7.8×10^{-10}
Impulsive noise power σ_w	-15 dB
Impulsive occurrence probability p	0.01
Gauss noise power σ_g	3.5 dB

$w_{i,\varsigma}$ can be estimated at a single AS by

$$w_{i,m} = \frac{\dfrac{1}{\left(M_{C42_{x_i}} - M_{C42_{x_\varsigma}}\right)^2 + \left(M_{C40_{x_i}} - M_{C40_{x_\varsigma}}\right)^2}}{\sum_{l=1}^{\Theta} \dfrac{1}{\left(M_{C42_{x_i}} - M_{C42_{x_l}}\right)^2 + \left(M_{C40_{x_i}} - M_{C40_{x_l}}\right)^2}}. \tag{42}$$

We use $P_{i|\varsigma}$ to represent $\Pr\left(M_{C40_x}, M_{C42_x}, \gamma_i|D = \mathcal{M}_\varsigma\right)$ at the line 4, which can be calculated with (39). Q is the maximum likelihood probability and D is the modulation identification result. Note that the SNR γ is obtained by

$$\gamma = \frac{\sum_{i=1}^{N} \mathbb{E}\left(|x_i|^2\right)}{\sum_{i=1}^{N} \mathbb{E}\left(|w|^2\right)}. \tag{43}$$

At the line 5 of Algorithm 1, the condition probability $\Pr\left(M_{C40_x}, M_{C42_x}|\gamma_i, D = \mathcal{M}_\varsigma\right)$ is multiplied by the weighting factor. The variable P indicates the likelihood of the modulation, which needs to be identified. By multiplying weighting factor, we strength the difference between various modulations, which can predictively improve the correct recognition rate (ACRR) and reduce the FPR.

With line 7 and line 8, we achieve maximum likelihood for the modulation, which needs to be identified. Hence, given a modulation M_m, the maximum likelihood can be estimated with

$$D = \arg\max_\varsigma \left\{\prod_{i=1}^{M} w_{i,\varsigma} \frac{\Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}\right)|\gamma_i, D = \mathcal{M}_\varsigma\right)}{\sum_{l=1}^{N_M} \Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}\right)|w_i, D = \mathcal{M}_l\right)}\right\}. \tag{44}$$

According to (38) and (44), we can present a metric to calculate the successful probability to recognize a modulation, called the average correct recognition rate, given by

$$P_{av} = \sum_{i=1}^{\Theta} \Pr\left(D = \mathcal{M}_i\,|\mathcal{M}_i\right) \Pr\left(\mathcal{M}_i\right). \tag{45}$$

In Algorithm. 1, we need to compute $P_{i|\varsigma}$, which equals to compute $\prod_{i=1}^{N} \Pr\left(\left(M_{C40_{x_i}}, M_{C42_{x_i}}, \gamma_i\right)\big|\,D = \mathcal{M}_\varsigma\right)$ with the complexity $O(\Theta \times M \times N^2 \times L)$. Furthermore, the computing complexity of $M_{C40_{x_i}}$ and $M_{C42_{x_i}}$ is $O(M \times N \times L)$. Finally, there are $O(\Theta \times M)$ loops in Algorithm 1. Therefore, the computation complexity of Algorithm 1 is $O(\Theta^2 M^2 N^2 L)$.

5. Simulations

In this section, we use MATLAB to build simulations for identifying frequently used modulations in PLC networks. The conditional probability distribution functions M_{C40}, $(k = 0, 2)$ are estimated when the γ is set from 0 dB to 20 dB. The simulation parameters for the PLC channel are chosen based on the HomePlug AV2 standard [27], which are configured as in Table 1. In Table I, the parameters g is the weighting factor of the PLC paths according to the Eq. (2) and η the number of paths from a transmitting port to a receiving port. a_0 and a_1 are the parameters in Eq. (3), and σ_g and σ_w are the powers of Gaussian noise and impulsive noise.

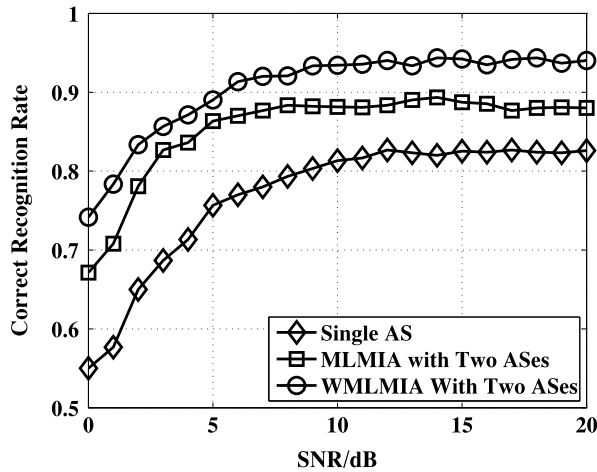**Fig. 6.** Comparison of recognition rate for classifier of 8PSK and 16QAM with three schemes, single AS, two ASes with ML and WML with two ASes.

Fig. 7. Comparison of recognition rate for classifier of BPSK, 4PAM of WML for three scenarios, single AS, WML with two ASes, and WML with three ASes.

Table 2
Results of modulation recognition.

Modulation	SNR = 5		SNR = 10	
	ACRR(%)	FPR(%)	ACRR(%)	FPR(%)
BPSK	92.82	6.84	94.85	2.00
4PSK	92.15	8.02	94.79	2.02
8PSK	91.97	8.52	94.22	2.76
4QAM	92.77	6.07	94.91	2.07
16QAM	92.96	7.63	95.07	3.03

ACRR: Average Correct Recognition Rate; FPR: False Positive Rate.

Here we evaluate the performance of the proposed algorithm WMCA by running the Monte-Carlo of PLC channel modeled according to the Table 1 for 1000 times to the generate simulation samples. The sample size for a signal is 500. Also, we use two FNs to transmit signals at the same time, and two (or three) ASes cooperatively receive these signals for recognizing their modulation.

Fig. 6 demonstrates the average correct recognition rate against the SNR of three the modulation identification algorithms, WMLMIA, maximum likelihood modulation identification algorithm (MLMIA), and the fourth order cumulants with single AS. In the simulation, the modulation is selected as 8PSK and 16QAM and the number of AS are set as two. The average correct recognition rate is calculated with the (45). We can observe that, compared to the algorithm with only one AS, the cooperative algorithm MLMIA with two ASes can improve the recognition rate around five percent. The reason is that more decision results on modulation from different ASes which can effectively remove some irregularly distributed data. Furthermore, when the weighting factors are introduced, about ten percent improvement is achieved on the correct recognition rate. The reason is that the weighting factors can make the difference from various sample collections more obvious, which improve the correct recognition rate.

Fig. 7 illustrates the recognizing performance of the different number of the involved ASs contributed to the algorithm WMLMIA. In the simulation, the modulations are selected as BPSK, 4PAM. According to Fig. 7, the correct recognition rate is enhanced significantly with the increasing the participated ASs number. However, we can see from the figure that with the increasing of the AS number, the increase of the ACRR drops. The reason is that the fourth order cumulants received from ASes tend to be the same with the increasing of the AS number. As a result, according to this simulation, three ASes can be enough for us to design a cooperative modulation identification system.
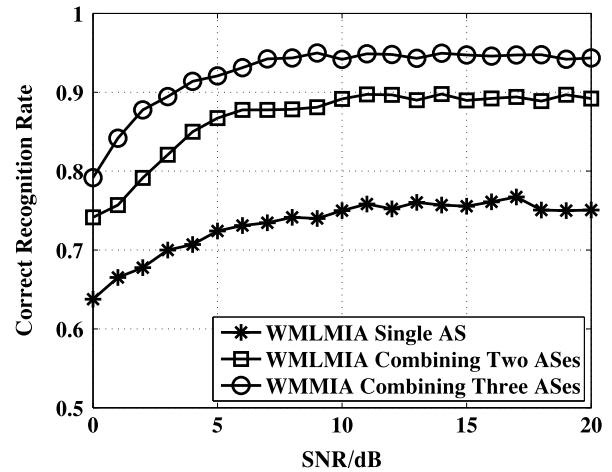
In our final simulation, the average correct recognition rate and the false positive rate are computed and listed in the Table 2 for five modulations i.e., BPSK, 4PAM, 4PSK, 8PSK, and 16QAM by adopting WMLMIA with 3 ASes. In the simulation, SNR of transmitting signals is set as 5 dB and 10 dB. As shown in Table 2, the average correct recognition rate is better than 91% as the SNR of transmitting signals is 5dB. Furthermore, if the SNR is set to 10 dB, the correct detection rate is higher than 94% with a false positive rate less than 4%. Hence, the modulation classification algorithm WMLMIA can be effectively used in practical PLC in-home networks.

6. Conclusions

In order to solve the problem of collecting information from PLC in-home sensor networks, we propose an automatic access scheme for sensors by identifying the modulation of signals. We improve the correct recognition rate by presenting a PLC-MIMO channel to aid different ASes exchanging the modulation identification information with the central server. By formulating the fourth-order cumulants, we propose to adopt the fourth-order cumulant for multiple users as the classifier's feature, which is especially fit for our cooperative identification systems. Based on the received characteristic information, we develop a weighting factor based recognition algorithm to recognize modulation of the signals. Simulation results affirm that the cooperative modulation recognition algorithm can significantly improve the correct recognition rate and reduce the false positive rate.

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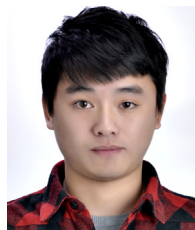
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