Initialization Procedure of Wireless Network Coding with Hierarchical Decode & Forward Strategy in Random Connectivity Networks

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Abstract. A Wireless Network Coding (WNC) a.k.a. a Physical Layer Network Coding in multi-source multi-node scenarios has shown its potential to increase network throughput compared to a communication based on an orthogonal separation of individual transmissions. In this paper we analyse necessary steps that have to be done to initialize the WNC communication including mainly establishing of relay operations. In our set-up a core network (we named it *a cloud*), that provides the WNC capabilities of reliable source – destination communication, starts its operation with no system state (connectivity) knowledge. Our goal is to design an algorithm that is capable to gain this information directly from the received constellation that is formed by the superposition of unknown number of transmitting sources with random channel realization and provide it to any cloud node. The algorithm has to be designed to work with the minimum demands on source node cooperation, the most of the functionality is laid upon the cloud.

Keywords: Physical Layer, Wireless Network Coding, Automatic Modulation Classification

1 Introduction and Related Work

Multi-source multi-node networks have attracted an interest of research community in recent years. For wired networks it was shown that the routing with orthogonally (in time, frequency, orthogonal code, hopping sequence, etc. or any of their combination) separated users is suboptimal in the terms of achievable capacity. Improvement of the network throughput can be achieved by a technique called a Network Coding (NC) [1], when the intermediate network nodes are capable to provide defined operations upon the incoming data instead of simple storing and forwarding. The NC was developed for wired network thus it assumes dedicated communication channels among the network nodes. The extension to the wireless environment is not a simple procedure. It introduces novel issues far different from the wired networks, especially natural broadcast behaviour, inherent superposition of the signals, unavoidable channel parametrization etc.

In recent years many authors try to develop techniques for the extension of the NC principle to the wireless networks. We call this extension a Wireless Network Coding (WNC) it is also known as a Physical Layer Network Coding (PLNC). Various signal processing schemes performed by the network nodes on the data were proposed. Strategies basically differ in the fact whether the intermediate nodes make or do not make a decision about some function of data. This leads to a variety of Decode/Compute/Amplify/Compress & Forward techniques [2–4]. Throughout this article we will consider one particular strategy named a Hierarchical Decode & Forward (HDF) [4] in unknown stochastic wireless connectivity scenario.

To the best of our knowledge any paper that deals with the initialization of the WNC procedure in stochastic unknown connectivity network is not known. All previous works assume a priori given network topology that is known to all network nodes, especially to the relays, that are able to utilize it when defining proper WNC operations. In a real world situation the source nodes are expected to be able to access the communication in an ad-hoc manner. The cloud is thus uncertain about the state of the network, e.g. the number of communicating nodes, the node connectivity and channel states are unknown. During the initialisation every inter-cloud node has to obtain the information mainly about the number of the sources in the neighbourhood together with their channel parametrization to be able to design its WNC operations properly. In the case of the WNC/HDF this mainly means establishing of proper relay input-output relation named a HDF map. Note that some kind of initialization (recovery of the unknown environment) in random connectivity networks is necessary for any other Decode/Compute/Amplify/Compress & Forward WNC technique.

A classical solution for ad-hoc networks is based on a dedication of individual source specific identification keys (addresses, pilot signals, training sequences etc.). This approach has a lot of drawbacks – the number of the sources is limited by the finite number of available resources that has to be distributed a priori to all source nodes. This needs a huge amount of the network coordination. The solution proposed in this paper tries to recover the necessary information with minimum source – cloud cooperation. Due to this the source can access the network, communicate and disconnect from the network selfishly, totally ignorant to any source in its neighbourhood. This property is very well suited to ad-hoc networks. Source identification sequences are also used but they are generated randomly and independently by the sources. These sequences do not need to be known at the receiving relay and serves only to recover uncertain network state. An Automatic Modulation Classification (AMC) is performed at the PHY layer over *the superimposed constellation that is random due to the random network topology and the random channel parametrization* to obtain the network state information. This solution can be seen as a non-coherent approach since no projection or match filtering of training sequences or pilot signals is performed. The very similar, but coherent, non-coordinated method is to dedicate the orthogonal identifications to the sources in a random way. Each cloud node performs a projection to the space of identifications in a step by step manner to recover what sources are included within the transmission and thus recover the necessary information to establish WNC/HDF mapping operation. The other possible solution is to design a network topology tolerant scheme based on random channel classes [5] that inherently deals with uncertain node connectivity at the cost of increased demands in the following communication steps.

It is important to note that the initialization procedure only provides necessary information to establish WNC/HDF communication – particularly the relay HDF maps has to be designed. No useful data payload is transmitted during this step. The useful data are transmitted in the consecutive stages with possibly far different modulation and coding schemes. The initialization procedure has to be repeated from time to time as the network state changes.

The rest if the paper is organised as follows. Section 2 provides the definitions and the model of the network. In section 3 the initialization of the cloud is formally described, this section also explain the necessity of the cloud initialization. K-means clustering and its application in the initialization process is described in section 4. Section 5 discuss the channel estimation abilities. The numerical results are presented in section 6 and the paper is concluded in section 7.

2 System Model and Background

Our wireless communication system consist of three elements – a set of N_S sources $\mathcal{S} = \{S_1, \cdots, S_i, \cdots, S_{N_S}\}$, a set of destinations $\mathcal{D}$ and of a wireless distributed self-organized entity named a cloud. The cloud is formed by N_R nodes $\mathcal{R} = \{R_1, \cdots, R_j, \cdots, R_{N_R}\}$ that are neither sources nor destinations. The key functionality of the cloud is to establish the reliable wireless connection between the sources and the destinations. See Fig.1.

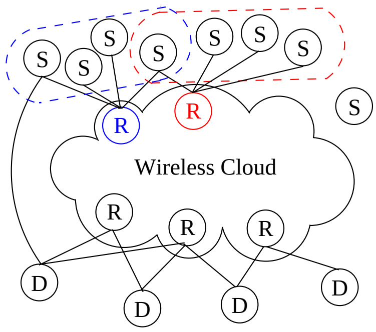


Fig. 1. Network topology

The cloud operations in our case are based on the Wireless Network Coding with the Hierarchical Decode & Forward strategy (WNC/HDF), HDF details are beyond the scope of this paper, [4] provides detailed formal description. This signal processing is a decode & forward type thus the relay makes the decision about the received signal. When the HDF strategy is applied the relay decided about the whole received superposition which jointly represents all of incoming transmissions. This forms a virtual hierarchical alphabet made of so called hierarchical symbols. But the concrete form of the hierarchical alphabet depends on the way how the signals are superposed, i.e. on the channel parametrization, individual source alphabets, number of the sources, etc.

For simplicity let us assume two sources communicating over the shared relay. Each source independently produces symbols c_A, c_B. The relay estimates the hierarchical symbol $\hat{c}_{AB}$ from the received superposition of the transmitted signals based on the extreme (e.g. max for simplicity) of some metric μ over all possible hierarchical symbols

$$\hat{c}_{AB} = \arg\max_{c_{AB}} \mu(c_{AB}) = \arg\max_{c_{AB}} \mu \left(\bigcup_{c_A, c_B : \mathcal{X}(c_A, c_B) = c_{AB}} \{c_A, c_B\} \right) \ . \tag{1}$$

Note that another possible relay strategy a Joint Decode & Forward (JDF) tries to estimate both individual sources from the received observation

$$[\hat{c}_A, \hat{c}_B] = \arg\max_{c_A, c_B} \mu(c_A, c_B) \ . \tag{2}$$

Hierarchical symbol is a joint representation of both individual data streams. If the hierarchical symbols are properly defined at the relay the destinations are able to recover the intended data by the help of the other observations. For simple one relay network the invertibility is formally given by an exclusive law [3, 4]. For multi-relay networks the exclusive law is generalized in [6].

3 Cloud Initialization Procedure

During a Cloud Initialization Procedure (CIP) the cloud has to obtain all necessary information to start its WNC/HDF operations. The number of active users has to be known to design the HDF maps. The knowledge of the states of the individual wireless channels can be utilised to avoid the MAC phase failures caused by the channel parametrization or the MAC phase can be based on a parameter invariant design of modulations [3, 7, 8].

At the early beginning of the WNC/HDF operation the cloud nodes are assumed to use the full HDF maps [4] to ease the establishing of the source – destination communication. The map cardinalities can be significantly reduced later as long as the condition of the WNC invertibility is met at the destinations.

When the full HDF map is used the cardinality of the relay output is given by the product of the incoming transmission signal cardinalities and corresponds to classical Multi-user PHY communications (e.g. 2-user MAC channel). Due to the practical reasons the maximum output cardinality is limited to low powers of two. Hence the number of the source nodes operated by one relay has to be limited too. This becomes very important for complex networks with multiple relay layers (when the outgoing relay transmission is processed by other relay(s)).

By $\mathcal{S}_j \subseteq \mathcal{S}$ we denote the set of sources operated by the j-th relay R_j. Number of sources operated by this relay is denoted $|\mathcal{S}_j| = L_j$. Because of the full HDF maps used in the initial phases of the WNC/HDF operation we limit the maximum number of sources per one relay to $L_{MAX} = 4$.

An example of two sets of the operated sources of two relays is depicted in Fig.1. It is important to note that two distinct sets $\mathcal{S}_i$ and $\mathcal{S}_j$ can have non empty intersection $\mathcal{S}_i \cap \mathcal{S}_j \neq \emptyset$ in fact to utilize all of the benefits of the WNC/HDF it is necessary that the source transmission passes through the cloud along several different paths.

Our aim is to design a tractable algorithm for the CIP that provides to the cloud all necessary information about the sources to start the WNC/HDF operations. The goal is to make this algorithm as blind as possible. We want to avoid any orthogonal solution, any solution that needs complex cooperation among the nodes and/or a solution guided by any form of a genie.

The proposed algorithm is based on the Automatic Modulation Classification (AMC). We try to recover required parameters directly from the received constellation that is formed by the superposition of unknown number of transmitting sources with random channel realization. An exhaustive overview of the single source AMC techniques can be found in [9]. To the best of the authors' knowledge any publication dealing with the multi-source AMC is not known.

The proposed CIP algorithm is based on a blind clustering of the received constellation by simple k-means algorithm [10]. The only a priori assumptions are the perfect time synchronization of the sources and the cloud and given limit of the number of the operated sources L_{MAX} (4 in our case).

Since the sources transmit within the same time, frequency and code subspace each relay $R_j \in \mathcal{R}$ receives the superposition of the transmissions

$$y_j(t) = \sum_{i:S_i \in \mathcal{S}_j}^{L_j} h_{ij} s_i(t) + w_j(t) \tag{3}$$

where $h_{ij} \in \mathbb{C}$ is the channel state between the source S_i and the relay R_j, $s_i(t)$ is the signal transmitted by the source S_i, $w_j(t)$ is the additive white Gaussian noise at the relay R_j with variance σ_w^2, L_j is the number of the sources operated by the relay R_j and the notation $i : S_i \in \mathcal{S}_j$ means such sources S_i that are operated by the relay R_j.

Throughout this paper we will assume a balance among the amplitudes of the channel states. $|h_{ij}|\ \forall i, j$ is a random variable with the uniform distribution on the closed interval $[0.5, 1]$. The channel phases $\angle h_{ij}\ \forall i, j$ are random variables with the uniform distribution on the closed interval $[0, 2\pi]$.

Constellation space model is

$$y_j[k] = \sum_{i:S_i \in \mathcal{S}_j}^{L_j} h_{ij} q_i[k] + w_j[k] \tag{4}$$

where k is used to index over the transmitted symbols and q_i are the channel symbols transmitted by the source S_i.

We define a signal to noise ratio (SNR) at the relay R_j by $\gamma_j = E[|Q_j|]^2/\sigma_w^2$, where $E[|Q_j|]^2$ is the energy of the superposition constellation which is a function of the number of the sources L_j, set of channel realizations $\{h_{ij}\}_{i:S_i \in \mathcal{S}_j}$ and the individual source channel alphabets $Q_i = \{q_i\}\ \forall i : S_i \in \mathcal{S}_j$. Operator $E[\cdot]$ denotes the expectation.

The CIP clustering algorithm works over the superposition constellation $Q_j(L_j, \{h_{ij}\}, Q_i) = \{q_j\}\ \forall i : S_i \in \mathcal{S}_j$ and tries to estimate the number of operated source L_j and the channel states $\{h_{ij}\}_{i:S_i \in \mathcal{S}_j}$ from it. To make the Q_j as simple as possible to ease the initialization the sources are assumed to utilize an On-Off Keying (OOK) modulation, i.e. $Q_i = \{0, 1\}\ \forall S_i \in \mathcal{S}$. Note again that during the CIP no useful data are transmitted, it serves only to resolve the uncertain network state.

After the reception of defined signalization (e.g. defined preamble) which serves only for timing synchronization from the cloud all synchronized sources start to simultaneously transmit the sequences of the OOK symbols. Due to the assumption of algorithm blindness the generated sequences are randomly and mutually independently drawn from the uniform distribution and thus no cooperation between the sources is needed. The relay R_j is expected to observe all 2^{L_j} constellation points of Q_j which is required by the clustering algorithm. This is guaranteed by the sufficient length of the transmission of the random sequence.

Define an event E meaning that the relay observes each constellation point of Q_j at least once. We want to find such a length of the sequence n_0 that guarantees $\Pr\{E\} \to 1$. This probability can be evaluated analytically by an inclusion-exclusion principle. Probability of the event E for various sequence length and various number of operated sources is plotted in Fig.2. One can see that the sequence length $n_0 = 150$ is sufficient for $\Pr\{E\} \to 1$ up to 4 (our L_{MAX}) operated users. For 4 sources and $n_0 = 150$ we have $\Pr\{E\} = 0.999$.

4 K-means Clustering

After the reception of n_0 length superimposed OOK sequences the relay R_j starts the clustering algorithm to estimate the number of operated users L_j and to estimate the set of the channel states $\{h_{ij}\}_{i:S_i \in \mathcal{S}_j}$. The algorithm is based on simple k-means algorithm [10] that proceeds in the following way:

Algorithm 1 k-means

Place l points (initial centroids) randomly into the space of all received symbols $y_j[k]$
while stop condition is not met **do**
  Assign each received point $y_j[k]$ to the closest centroid
  New centroids $\leftarrow$ points that minimize sum of squared inter-cluster distances
end while

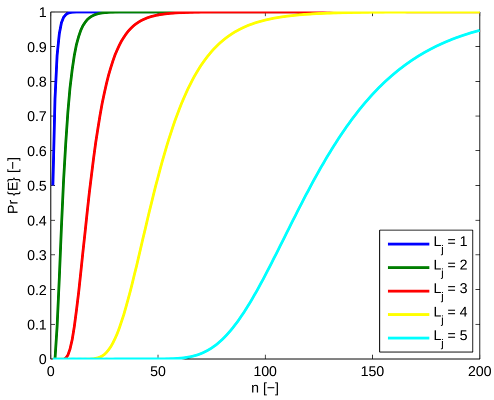


Fig. 2. Probability of the event E.

The algorithm returns the position of the l centroids $\{c^{(1)}, \cdots, c^{(l)}\}$ and the identification to which cluster each received point belongs to. In the case of the signal space the used metric is the Euclidean distance. Although the k-means algorithm guarantees the termination the optimal solution is not guaranteed at all. The algorithm may converge to local optimum [10].

The correct number of clusters l is not known a priori since it is a function of the unknown number of the operated sources as well as the channel parametrization, i.e. $l(L_j, \{h_{ij}\}_{i:S_i \in \mathcal{S}_j})$. Thus we start k-means with different number of the clusters l from 1 to $2^{L_{MAX}}$. For some particular channel states some points in Q_j can fall close to or even upon each other and thus will be grouped into the same cluster. We choose the number of clusters l_{best} that fits best to the received constellation. The criterion is the minimum distance to all centroids, i.e. the total sum of the squared Euclidean distances among the centroids and the points corresponding to their clusters

$$d_{sum}(l) = \sum_{a=1}^{l} \sum_{b:y[b] \in c^{(a)}} |y[b] - c^{(a)}|^2 \tag{5}$$

where $b : y[b] \in c^{(a)}$ denotes received signal space points $y[b]$ that belong to the cluster with the centroid $c^{(a)}$.

The maximum possible number of distinct constellation points of Q_j is given by 2^{L_j}. The minimum number depends on concrete channel parametrizations, obviously the minimum is achieved when the channel gains h_{ij} are collinear and their amplitudes are constant $|h_{ij}| = \text{const}$. For example two operated sources can produce up to four points – $Q_j = \{0, h_{1j}, h_{2j}, h_{1j} + h_{2j}\}$, see Fig.3a. Three distinct points can also happen – $Q_j = \{0, h_{1j}, h_{1j}, 2h_{1j}\}$ if $h_{1j} = h_{2j}$ or $Q_j = \{0, h_{1j}, -h_{1j}, 0\}$ if $h_{1j} = -h_{2j}$, see Fig.3b. It is important to note that the minimum number of the points cannot be arbitrary low, e.g. constellation with only two points for two operated sources is not possible. Remind that we do not allow $|h_{ij}|$ to go to zero.

Since the significant decrease of the number of the distinct constellation points of Q_j happens rarely we decide to estimate the number of operated sources by $\hat{L}_j = \lceil \log_2(l_{best}) \rceil$, where l_{best} is the number of the clusters that approximate the received constellation with the minimal $d_{sum}(l)$ among all possible l.

The CIP algorithm works in the following way:

Algorithm 2 CIP Clustering

Receive $y_j[k]$ $k \in \{1, \cdots, n_0\}$
Set the threshold d_{th} based on the SNR γ_j
Set the number of the repetitions of the k-means r_{MAX}
for $l = 1 \to 2^{L_{MAX}}$ **do**
  for $r = 1 \to r_{MAX}$ **do**
    perform the k-means over $y_j[k]$ $\forall k$ with l clusters
  end for
  remember the clustering with the minimal $d_{sum}(l)$
end for
$l_{best} \leftarrow$ Find the first l with $d_{sum}(l) \leq d_{th}$
if $d_{sum}(l) > d_{th}$ $\forall l$ **then**
  $l_{best} = 2^{L_{MAX}}$
end if
return $\hat{L}_j = \lceil \log_2(l_{best}) \rceil$
return $\{c\}_{best} = \left\{ c_{best}^{(1)}, \cdots c_{best}^{(l_{best})} \right\}$

The threshold value d_{th} depends on the SNR of received constellation γ_j as well as on the desired probability of correct detection. Fig.5 shows the probability of the correct detection of the number of the operated sources for various values of d_{th} as a function of the SNR. These curves can be used for adaptive choice of the d_{th} value based on the actual SNR to achieve the desired probability of the correct detection.

The application of the threshold value to obtain the best clustering is necessary due to the obvious property of the k-means algorithm – generally the higher the number of the clusters l the lower the $d_{sum}(l)$ can be. Evidently the best possible clustering (in terms of the minimal $d_{sum}(l)$) is the one when each cluster contains exactly one data point that coincides with the centroid of its cluster, i.e. $c^{(i)} = y[i]$ $\forall i$, this leads to $d_{sum} = 0$. Having the threshold value (according to the SNR and the desired probability of the correct detection) we choose the first solution with $d_{sum}(l) \leq d_{th}$ so as not to "over-cluster" the received data.

5 Channel Estimation Capabilities

From the estimation of the best position of the centroids $\{c\}_{best}$ the relay is able to estimate the channel states. Received superposition constellation Q_j

is formed by all possible binary linear combinations of the channel states, see Eq.(4). Estimation of the channel states can be described by the simple matrix equation

$$\mathbb{A}\mathbf{h}_j = \mathbf{b} \tag{6}$$

where $\mathbb{A}$ is a $(2^{\hat{L}_j} - 1) \times \hat{L}_j$ matrix of all possible non-zero binary $\hat{L}_j$-tuples, $\mathbf{h}_j = [h_{1j}, \cdots, h_{\hat{L}_j j}]^T$ is a vector of unknown channel states from $\hat{L}_j$ operated sources and the right-hand side vector $\mathbf{b}$ is an unknown ordering (possibly with repetitions of some elements) of the centroid positions $\{c\}_{best}$.

The goal is to find an appropriate ordering of the right-hand side vector $\mathbf{b}$. We illustrate this on a simple $L_j = 2$ example, see Fig.3a. By application of Algorithm 2 we obtain the correct estimate of the number of the operated source $\hat{L}_j = L_j = 2$ because the best clustering is the one with $l = 4$. We also obtain the positions of the centroids $\{c^{(1)}, c^{(2)}, c^{(3)}, c^{(4)}\}$ (red crosses in Fig.3a). One of them, let us say $c^{(4)}$, corresponds to the transmission of the zero OOK symbols and bears no information about the channel state.

In this example the particular form of Eq.(6) is

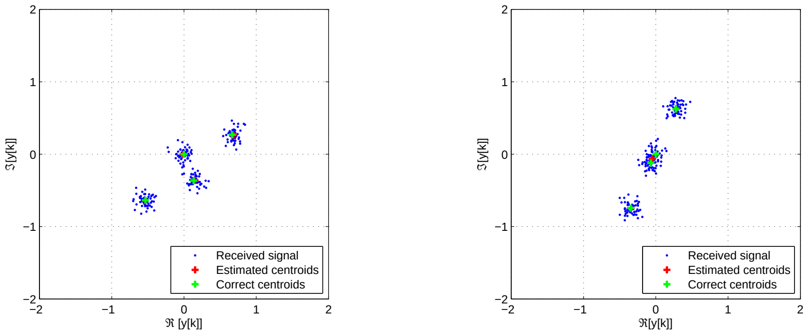
$$\begin{pmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} h_{1j} \\ h_{2j} \end{pmatrix} = \begin{pmatrix} c^{(u)} \\ c^{(v)} \\ c^{(w)} \end{pmatrix} \quad . \tag{7}$$

The goal is to find a proper assignment between the estimated cluster centroids $\{c^{(1)}, c^{(2)}, c^{(3)}\}$ and its ordering $\{c^{(u)}, c^{(v)}, c^{(w)}\}$. From Eq.((7)) it is obvious that we seek a pair of centroids that summed together gives the third one. If the solution is for example $c^{(1)} + c^{(2)} = c^{(3)}$ then $c^{(1)}$ and $c^{(2)}$ equals to h_{1j} and h_{2j}. Note that there is an ambiguity because we are not able to distinguish which channel parametrization belongs to which source. But this ambiguity can be neglected for symmetric HDF maps.

Similar procedure can be extended to more than two operated sources. But the assumption of the symmetric HDF maps is very strict and the channel estimation capabilities have to be deeply investigated.

6 Numerical Results

We have implemented the proposed Algorithm 2 in MATLAB and numerically evaluate its properties in various scenarios (number of operated sources, random channels, impact of the threshold level, etc.). The simulations mainly test the abilities of the CIP to correctly estimate the number of the communicating sources under random channel parametrizations. All simulations were performed with the following parameters: the random OOK sequence length $n_0 = 150$, the number of the repetitions of the k-means algorithm $r_{MAX} = 5$ and the maximum number of the operated sources $L_{MAX} = 4$. Figs.3a, 3b and 4 show the example results after the clustering of the received superposition of the randomly generated 150 symbols long OOK sequences with two respectively three sources for random channel parametrizations. Fig.3a shows the correct clustering in the case of two sources. The incorrect clustering is depicted in Fig.3b. Here the channel parametrizations cause two points of Q_j to fall close to each other and thus to be clustered within one cluster. It is important to note that the number of the operated sources is correctly estimated in this situation due to $\hat{L}_j = \lceil \log_2(l_{best}) \rceil$. On the other hand the incorrect clustering will complicate the channel estimation procedure and also the estimation error will increase. Fig.4 shows the correct clustering of the signal from three operated sources.



(a) Successful clustering $\gamma_j = 15$dB. (b) Unsuccessful clustering $\gamma_j = 15$dB.

Fig. 3. Two source clustering

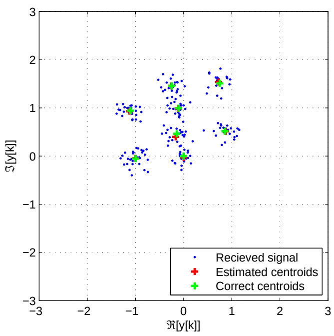


Fig. 4. Three sources - successful clustering $\gamma_j = 15$ dB.

The performance of the CIP algorithm is significantly determined by the choice of the threshold value d_{th}. Fig.5 shows the probability of the correct estimation of the number of the operated sources parametrized by the threshold value, i.e. $\Pr\{L_j = \hat{L}_j | d_{th}\}$. The proposed algorithm achieves approximately

97% probability of the correct detection of the number of the operated sources at the high SNR regime. The optimal d_{th} is close to 3. At the lower SNRs the high probability of correct estimation can be achieved by adaptive selection of the threshold value according to the actual SNR.

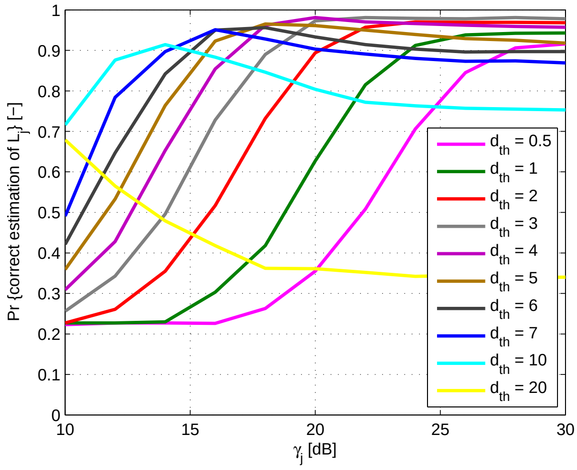


Fig. 5. Probability of the correct estimation of the number of the sources.

7 Conclusions

In this paper we design a simple blind non-coherent algorithm that provides the estimation of the number of the operated sources to every cloud relay node. This knowledge is necessary for the proper design of the WNC/HDF operation at each relay. The proposed algorithm works in the distributed way and needs no cooperation between the sources. The only a priori assumption is the perfect time synchronization of the cloud that is revealed to the sources. The received superposition of known alphabets (but the number of the sources and the channel parametrization are unknown) is processed by the clustering algorithm based on the k-means. From the results of this clustering the number of operated sources is estimated and the position of the resulting centroids can serve for the channel estimation.

The algorithm is tested in scenarios that take into account the practical aspects of the wireless cloud entity. The numerical simulations show that the high probability (at about 97%) of the correct detection can be achieved at the high SNR regime in the AWGN channel with the properly set threshold value. At the lower SNR regime the threshold value can be adaptively optimized based on the measurement of SNR to maximize the probability of the correct detection.

Acknowledgement

Work in this paper was supported by the European Science Foundation through FP7-ICT SAPHYRE project the Grant Agency of the Czech Republic, grant 102/09/1624, the Ministry of education, youth and sports of the Czech Republic grant LD12062 and by the Grant Agency of the Czech Technical University in Prague, Grants no. SGS10/287/OHK3/3T/13 and SGS12/076/OHK3/1T/13.

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