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A Nonlinear Relay Scheme Resilient to Interference with Unknown CSI

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***Abstract*—This paper studies relay networks under interferences, and proposes a *nonlinear* amplify-and-forward (NAF) scheme for interference suppression. In contrast to the existing *linear* amplify-and-forward (AF) relay schemes, the proposed NAF scheme adopts hyperbolic signal amplitude compression for the instantaneous constraint on the transmit power of each antenna of the relay nodes. Noting the striking similarities between the relay network and a three-layer artificial neural network (ANN), we propose a NAF relay scheme inspired by the back-propagation algorithm (NAF-BP) to optimize the weights of the destination and the relay nodes, according to the minimum mean square error (MMSE) criterion. The NAF-BP scheme assumes no channel state information (CSI), no data exchange between the relay nodes, except for a backward channel from the destination to the relays. We also further develop a centralized benchmark algorithm for the NAF relay scheme using the sequential convex programming (SCP), which we refer to as the NAF-SCP. The effectiveness of the proposed scheme is verified through extensive simulations.**

***Index Terms*—relay schemes; interference suppression; instantaneous power constraint; back-propagation algorithm;**

I. Introduction

Relay nodes are usually employed for overcoming the severe propagation attenuation between the source and the destination [1]–[3]. Having multiple distributed relay nodes can potentially provide benefits more than just enhancing signal and extending communication distance; they can even cooperate as a virtual array for interference suppression.

In the presence of uncooperative interferences, the cooperation between the relay nodes is difficult. Although interferences become ubiquitous owing to the ever-increasingly crowded frequency spectrum, the literature on interference-resilient relay networks is scarce, and it is for good reasons. One may presumably think that the nodes need to have the global channel state information (CSI) and even to exchange their received samples for cooperative beamforming. For example, in [4] the authors apply a compressed and forward (CF) scheme for inter-cell interference suppression, assuming that the destination and the relay share the perfect CSI to obtain a coordinate ascent algorithm.

To the best of our knowledge, the problem of optimizing a relay network under interferences but without CSI, albeit practically interesting, has not ever been addressed in the literature except for our previous work in [5]. In the same vein as our work in [5], in this paper we attempt to attack this difficult problem using a novel nonlinear amplify and forward (NAF) scheme.

But the work in [5] uses the PA's nonlinear modulation upon the analog signal for *instantaneous amplitude* limitation of the transmit signal, which may cause frequency spectrum leakage. In this paper, we propose a nonlinear hyperbolic signal-amplitude-compression model for instantaneous power limitation of the digital signal so that the analog signal will not enter the nonlinear region of the PA, thus preventing spectrum leakage due to the nonlinearity of the PA. Most existing works, however, only consider the average power constraint, including the constraint of the total transmit power of all relay nodes [3], [6], [7] and the constraint of the transmit power of each individual relay node [3], [7], [8], probably because the instantaneous power limitation can impose a major difficulty to the relay design.

We observe that a NAF relay network is strikingly similar to a three-layer artificial neural network (ANN). Based on this observation, we optimize the NAF relay network using a Back-Propagation (BP) inspired algorithm [5], which is referred to as the NAF-BP. The NAF-BP algorithm attempts to minimize the mean squared error (MSE) between the output of the destination and the pilot sequence, with respect to the processing coefficients of the destination and the relay nodes, which leads to a fully-distributed and interference-resilient algorithm that requires no explicit channel information. In contrast, most existing works on the (interference-free) relay networks assume a global CSI is known to the relay nodes, precisely or imperfectly, see, e.g., [3], [8], [9].

To gauge the performance of the proposed scheme, we introduce a benchmark, which assumes that a central node has all the global information and applies the sequential convex programming (SCP) [10] to jointly optimize all the coefficients of the destination and the relay nodes, which we refer to as the SCP-based algorithm for the NAF relay scheme (NAF-SCP). We compare the NAF-BP algorithm with the benchmark in the numerical simulations and find that they may achieve the same performance. Even in an interfere-free environment, the NAF-SCP algorithm can outperform the *linear* beamforming scheme in [8], although the latter assumes an average power constraint, more relaxed one than the instantaneous power constraint.

II. System Model and Problem Formulation

A. System Model

We consider the relay network as shown in Fig. 1, which consists of one single-antenna source, one M_d-antenna desti-

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nation, and N relay nodes each equipped with M_r receiving antennas and one transmitting antenna.

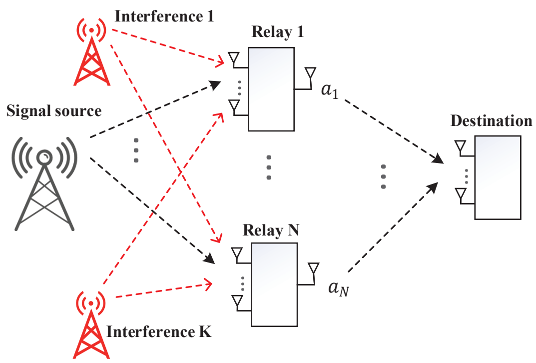

Fig. 1: A relay network under interferences.

As the source transmits signal $s(i)$, the n-th relay node ($n = 1, \ldots, N$) receives

$$\mathbf{r}_n(i) = \mathbf{h}_n s(i) + \mathbf{G}_n \mathbf{z}(i) + \boldsymbol{\eta}_n(i), i = 1, 2, 3, \cdots \quad (1)$$

where $\mathbf{h}_n \in \mathbb{C}^{M_r}$ and $\mathbf{G}_n \in \mathbb{C}^{M_r \times K}$ represent the channel from the source and the K interferences $\mathbf{z}(i) \in \mathbb{C}^K$ to the relay, respectively, and $\boldsymbol{\eta}_n \sim \mathcal{CN}(0, \sigma_r^2 \mathbf{I})$ is the thermal noise.

To avoid self-interference, the relay nodes work in the frequency division duplex (FDD) mode. Denote $f_n(\cdot)$ as the processing function and $a_n = f_n(\mathbf{r}_n)$ as the output of the n-th relay node. Stack the transmitted signals of all relay nodes into $\mathbf{a} = [a_1, \ldots, a_N]^T$. The destination receives

$$\mathbf{y} = \mathbf{H}_d \mathbf{a} + \boldsymbol{\eta}_d, \quad (2)$$

where $\mathbf{H}_d \in \mathbb{C}^{M_d \times N}$ is the channel between the N relays and the destination, and $\boldsymbol{\eta}_d \sim \mathcal{CN}(0, \sigma_d^2 \mathbf{I})$ is the noise. Here and in the sequel, we omit the time index i for notational simplicity.

Applying the equalization function $f_d(\cdot)$ to the received signal, the destination yields $\hat{s} = f_d(\mathbf{y})$.

As the CSI $\mathbf{h}_n$, $\mathbf{G}$ and $\mathbf{H}_d$ are unknown, we rely on the pilot sequences to optimize the equalization/processing function of the destination and relay nodes by minimizing the MSE

$$\min_{\{f_n(\cdot)\}_{n=1}^N, f_d(\cdot)} \mathbb{E} \left| \hat{s} - s \right|^2, \quad (3)$$

which amounts to maximizing the output signal-to-interference-plus-noise ratio (SINR), because [11]

$$\mathsf{SINR} = \frac{1}{\mathsf{MSE}} - 1. \quad (4)$$

B. The Nonlinear Amplify-and-Forward (NAF) Scheme

We draw analogies between a relay network and an ANN as follows. The source, the destination, and the relay nodes in Fig. 1 are analogous to the neurons in the different layers of the ANN in Fig. 2. The input into a neuron in the l-th layer is a weighted sum (with the weights $\omega_{nk}^{(l)}$) of the outputs of the neurons in the $(l-1)$-th layer. Similarly, each relay node applies a beamforming weight $\mathbf{v}_n \in \mathbb{C}^{M_r}$ to the received signal $\mathbf{r}_n$ in (1), namely

$$b_n \triangleq \mathbf{v}_n^H \mathbf{r}_n. \quad (5)$$

Taking into account the practical constraint of the instantaneous transmit power of the relay nodes, we propose a *nonlinear* hyperbolic signal-amplitude-compression model σ,

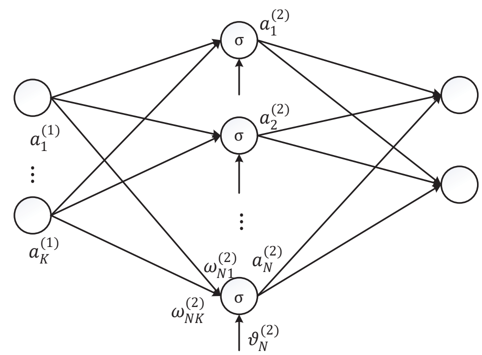

Fig. 2: The topology of a three-layer ANN.

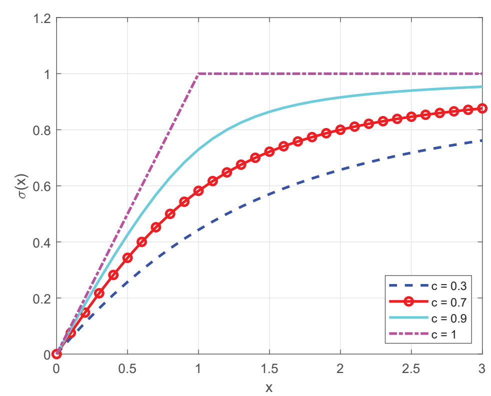

Fig. 3: The hyperbolic signal-amplitude-compression model.

$$\sigma(x) = \frac{1}{2} \left[x + 2 - c - \sqrt{(x-c)^2 + 4 - 4c} \right], \quad (6)$$

where the parameter c regulates the curvature of the hyperbola as shown in Fig. 3.

Each relay node processes the signal b_n as

$$a_n = \sigma(|b_n|) e^{j \angle b_n}, \quad (7)$$

where $\angle b_n$ is the phase of b_n.

The transmitted signal a_n in (7) is analogous to the output $a_n^{(l)}$ in Fig. 2; the hyperbolic model σ is analogous to the activation function σ (such as a Rectified Linear Unit) in Fig. 2. But here we allow for complex inputs, while a standard ANN operates in the real domain. Moreover, the hyperbolic model limits the peak power to be no greater than one, which can help improve the PA's energy efficiency. Note that here the nonlinear mapping is applied to the digital signal, whereas in [5] the nonlinear mapping is conducted in the analog PA.

The destination applies an equalizer to the received signal

$\mathbf{y}$ in (2) as

$$\hat{s} = \mathbf{w}^H \mathbf{y}. \tag{8}$$

Given the NAF relay network architecture, (3) amounts to

$$\min_{\mathbf{w},\{\mathbf{v}_n\}_{n=1}^N} \mathbb{E}\left| \mathbf{w}^H \left\{ \mathbf{H}_d \begin{bmatrix} \sigma(|\mathbf{v}_1^H \mathbf{r}_1|)e^{j\angle b_1} \\ \vdots \\ \sigma(|\mathbf{v}_N^H \mathbf{r}_N|)e^{j\angle b_N} \end{bmatrix} + \boldsymbol{\eta}_d \right\} - s \right|^2. \tag{9}$$

Although to solve (9) appears difficult, especially when the CSI is unknown, we can apply a distributed algorithm [5] to solve the problem, as explained in the following.

III. A Back-Propagation Inspired Algorithm for the NAF Relay Scheme (NAF-BP)

In a similar vein to the least mean square (LMS) approach, we use a single realization $J \triangleq |\hat{s} - s|^2$ instead of (9) as the cost function. The derivations below are essentially the same as that in [5, Section III], except for the different nonlinear activation function.

Using (8) and the chain rule, we obtain the derivatives of J with respect to the coefficients of the destination as

$$\frac{\partial J}{\partial \mathbf{w}^*} = \left(\frac{\partial \hat{s}}{\partial \mathbf{w}^*}\right) \frac{\partial J}{\partial \hat{s}} = \mathbf{y}\left(\hat{s} - s\right)^*. \tag{10}$$

With (2), (8) and (10), we obtain

$$\frac{\partial J}{\partial a_n^*} = \left(\frac{\partial \hat{s}^*}{\partial a_n^*}\right) \frac{\partial J}{\partial \hat{s}^*} = \mathbf{h}_{d,n}^H \mathbf{w}\left(\hat{s} - s\right), \tag{11}$$

where $\mathbf{h}_{d,n} \in \mathbb{C}^{M_d}$ is the n-th column of $\mathbf{H}_d$.

From (7) and (11) we have

$$\frac{\partial J}{\partial b_n^*} = \frac{\partial J}{\partial a_n^*}\frac{\partial a_n^*}{\partial b_n^*} + \frac{\partial J}{\partial a_n}\frac{\partial a_n}{\partial b_n^*}, \tag{12}$$

where $\frac{\partial a_n}{\partial b_n^*} = \frac{1}{2}\left[\nabla\sigma\left(|b_n|\right) - \frac{|a_n|}{|b_n|}\right] e^{j2\angle b_n}$, $\frac{\partial a_n^*}{\partial b_n^*} = \frac{1}{2}\left[\nabla\sigma\left(|b_n|\right) + \frac{|a_n|}{|b_n|}\right]$, and $\nabla\sigma\left(x\right) \triangleq \frac{\partial \sigma(x)}{\partial x} = \frac{1}{2} - \frac{x-c}{2\sqrt{(x-c)^2+4-4c}}$.

According to (5) and (12), we obtain the derivatives of J with respect to the coefficients of the relay nodes as

$$\frac{\partial J}{\partial \mathbf{v}_n^*} = \frac{\partial b_n}{\partial \mathbf{v}_n^*}\left(\frac{\partial J}{\partial b_n^*}\right)^*. \tag{13}$$

The derivatives in (10) and (13) can be used as the update directions of the coefficients, which are the gradients based on a single sample $s(i)$. For an L-length pilot sequence, we have

$$\overline{\mathrm{d}}_x = \frac{1}{L}\sum_{i=1}^{L}\frac{\partial J}{\partial x^*}(i),\ x \in \{\mathbf{w}, \{\mathbf{v}_n\}_{n=1}^N\}. \tag{14}$$

Furthermore, for T sets of pilot sequences, we can use the momentum method [12] to update the coefficients as

$$x(t) = x(t-1) - \alpha \mathrm{d}_x(t),\ t = 1, 2, ...T, \tag{15}$$

where $\alpha \in (0,1)$ is the learning rate, and $\mathrm{d}_x(t) = \lambda \mathrm{d}_x(t-1) + (1-\lambda)\overline{\mathrm{d}}_x(t)$ with $\mathrm{d}_x(0) = 0$ and $\lambda \in (0,1)$.

Note that in the ANN in Fig. 2, a neuron is only connected to those in the adjacent layers but not to its peers in the same layer. Similarly, the NAF-BP scheme uses the received signal from the source and the feedback from the destination, while having no data exchange with the peer relay nodes.

In addition, according to (11)-(13), the n-th relay node only needs to obtain $\mathbf{h}_{d,n}^H \mathbf{w}(\hat{s} - s)$ from the external for updating the weight $\mathbf{v}_n$. Let the destination broadcast $\left[\mathbf{w}(\hat{s} - s)\right]^*$ to the relays through the reverse channel, then the n-th relay can receive $\mathbf{h}_{d,n}^T \left[\mathbf{w}(\hat{s} - s)\right]^*$ and update its weight without explicit CSI.

IV. A SCP-based Algorithm for the NAF Relay Scheme (NAF-SCP)

In the previous section, we have developed the NAF-BP algorithm, which is suitable for distributed implementation. To gauge the performance limit of the proposed nonlinear scheme, we present a SCP-based centralized algorithm for the NAF relay scheme, which neglects any implementational hindrance, such as the causality, the overhead for inter-node cooperation, and the computational complexity.

Recalling (9), we integrate an L-length pilot sequence to be

$$\min_{\mathbf{w},\{\mathbf{v}_n\}_{n=1}^N} \sum_{l=1}^{L}\left| \mathbf{w}^H \left\{ \mathbf{H}_d \begin{bmatrix} \sigma(|\mathbf{v}_1^H \mathbf{r}_{1l}|)e^{j\angle b_{1l}} \\ \vdots \\ \sigma(|\mathbf{v}_N^H \mathbf{r}_{Nl}|)e^{j\angle b_{Nl}} \end{bmatrix} + \boldsymbol{\eta}_{dl} \right\} - s_l \right|^2 \tag{16}$$

Denoting all transmitted signals of the relay nodes as $\mathbf{A} = [\mathbf{a}_1 \cdots \mathbf{a}_N] \in \mathbb{C}^{L\times N}$ with [cf. (7)]

$$a_{nl} = \sigma\left(|\mathbf{v}_n^H \mathbf{r}_{nl}|\right) e^{j\angle b_{nl}}, \tag{17}$$

we transform the objective function in (16) into

$$\min_{\mathbf{w},\{\mathbf{v}_n\}_{n=1}^N} \left\|\mathbf{A}\mathbf{H}_d^T \mathbf{w}^* - \mathbf{s} + \tilde{\boldsymbol{\eta}}^T \mathbf{w}^*\right\|^2, \tag{18}$$

where $\mathbf{s} = [s_1, \cdots, s_L]^T$, $\tilde{\boldsymbol{\eta}} = [\boldsymbol{\eta}_{d1}, \ldots, \boldsymbol{\eta}_{dL}] \sim \mathcal{CN}(0, L\cdot\sigma_d^2\mathbf{I})$, and $\mathbf{1}$ represents an $L\times 1$ vector of all ones.

Since the signal and noise are independent, we optimize the NAF relay transmission according to

$$\min_{\mathbf{w},\{\mathbf{v}_n\}_{n=1}^N} C \triangleq \left\|\mathbf{A}\mathbf{H}_d^T \mathbf{w}^* - \mathbf{s}\right\|^2 + L\cdot\sigma_d^2\|\mathbf{w}\|^2. \tag{19}$$

Equating $\frac{\partial C}{\partial \mathbf{w}^*} = 0$, we obtain the optimal weight of the destination node as

$$\mathbf{w} = \left(\mathbf{H}_d \mathbf{A}^T \mathbf{A}^* \mathbf{H}_d^H + L\cdot\sigma_d^2 \mathbf{I}\right)^{-1} \mathbf{H}_d \mathbf{A}^T \mathbf{s}^*. \tag{20}$$

With $\mathbf{w}$ being fixed, we attempt to

$$\min_{\{\mathbf{v}_n\}_{n=1}^N} \tilde{C} \triangleq \left\|\mathbf{A}\mathbf{H}_d^T \mathbf{w}^* - \mathbf{s}\right\|^2, \tag{21}$$

where $\{\mathbf{v}_n\}_{n=1}^N$ are all in $\mathbf{A}$ (see (17) for details).

The derivative of the cost function $\tilde{C}$ with respect to the output of the n-th relay is $\frac{\partial \tilde{C}}{\partial \mathbf{a}_n} = \mathbf{h}_{d,n}^T \mathbf{w}^* \left(\mathbf{A}\mathbf{H}_d^T \mathbf{w}^* - \mathbf{s}\right)^* \in \mathbb{C}^L$. Denoting $\frac{\partial \tilde{C}}{\partial \mathbf{b}^*} \triangleq \left[\left(\frac{\partial \tilde{C}}{\partial \mathbf{b}_1^*}\right)^T, \cdots, \left(\frac{\partial \tilde{C}}{\partial \mathbf{b}_N^*}\right)^T\right]^T \in \mathbb{C}^{NL}$, we obtain the l-th element of $\frac{\partial \tilde{C}}{\partial \mathbf{b}_n^*}$ as

$$\frac{\partial \tilde{C}}{\partial b_{nl}^*} = \frac{\partial \tilde{C}}{\partial a_{nl}} \frac{\partial a_{nl}}{\partial b_{nl}^*} + \left(\frac{\partial \tilde{C}}{\partial a_{nl}} \right)^* \frac{\partial a_{nl}^*}{\partial b_{nl}^*}, \tag{22}$$

where $\frac{\partial a_{nl}^*}{\partial b_{nl}} = \left(\frac{\partial a_{nl}}{\partial b_{nl}^*} \right)^*$ and $\frac{\partial a_{nl}}{\partial b_{nl}} = \frac{\partial a_{nl}^*}{\partial b_{nl}^*}$.

Denote the second derivative $\frac{\partial^2 \tilde{C}}{\partial \mathbf{b} \partial \mathbf{b}^H}$ as a partitioned matrix whose (n,m)-th $(m = 1, \cdots, N)$ block $\left[\frac{\partial^2 \tilde{C}}{\partial \mathbf{b} \partial \mathbf{b}^H} \right]_{nm} = \frac{\partial^2 \tilde{C}}{\partial \mathbf{b}_n \partial \mathbf{b}_m^H} \in \mathbb{C}^{L \times L}$. Obviously, $\frac{\partial^2 \tilde{C}}{\partial \mathbf{b}_n \partial \mathbf{b}_m^H}$ is a diagonal matrix and its l-th diagonal element $\left[\frac{\partial^2 \tilde{C}}{\partial \mathbf{b}_n \partial \mathbf{b}_m^H} \right]_l$ is

$$\frac{\partial^2 \tilde{C}}{\partial b_{nl} \partial b_{ml}^*} = \begin{cases} |\mathbf{h}_{d,n}^T \mathbf{w}^*|^2 \left(\left| \frac{\partial a_{nl}}{\partial b_{nl}^*} \right|^2 + \left| \frac{\partial a_{nl}}{\partial b_{nl}} \right|^2 \right) & \\ \quad + 2 \cdot \Re\{ \frac{\partial \tilde{C}}{\partial a_{nl}} \frac{\partial^2 a_{nl}}{\partial b_{nl} \partial b_{nl}^*} \} & n = m \\ \mathbf{h}_{d,m}^T \mathbf{w}^* \mathbf{h}_{d,n}^H \mathbf{w} \frac{\partial a_{nl}^*}{\partial b_{nl}} \frac{\partial a_{ml}}{\partial b_{ml}^*} & \\ \quad + \mathbf{h}_{d,m}^H \mathbf{w} \mathbf{h}_{d,n}^T \mathbf{w}^* \frac{\partial a_{nl}}{\partial b_{nl}} \frac{\partial a_{ml}^*}{\partial b_{ml}^*} & n \neq m \end{cases}, \tag{23}$$

where $\frac{\partial^2 a_{nl}}{\partial b_{nl} \partial b_{nl}^*} = \frac{1}{4} \left[\nabla^{(2)} \sigma (|b_{nl}|) + \frac{\nabla \sigma (|b_{nl}|)}{|b_{nl}|} - \frac{|a_{nl}|}{|b_{nl}|^2} \right] e^{j \angle b_{nl}}$ with $\nabla^{(2)} \sigma (x) \triangleq \frac{\partial^2 \sigma(x)}{\partial^2 x} = \frac{2c-2}{[(x-c)^2+4-4c]^{\frac{3}{2}}}$, and $\Re\{\cdot\}$ stands for taking the real part.

Let $\mathbf{R} = \mathrm{diag}(\mathbf{R}_1, \cdots, \mathbf{R}_N)$ be a $NM_r \times NL$ block diagonal matrix, where $\mathbf{R}_n = [\mathbf{r}_{n1}, \cdots, \mathbf{r}_{nL}] \in \mathbb{C}^{M_r \times L}$. With (22) and (23), we can get the first and second derivatives of the cost function $\tilde{C}$ in (21) with respect to the weights $\mathbf{V} = \left[\mathbf{v}_1^T, \cdots, \mathbf{v}_N^T \right]^T$ of the relay nodes as

$$\frac{\partial \tilde{C}}{\partial \mathbf{V}^*} = \mathbf{R} \left(\frac{\partial \tilde{C}}{\partial \mathbf{b}^*} \right)^*, \tag{24}$$

and

$$\frac{\partial^2 \tilde{C}}{\partial \mathbf{V} \partial \mathbf{V}^H} = \left(\mathbf{R} \frac{\partial^2 \tilde{C}}{\partial \mathbf{b} \partial \mathbf{b}^H} \mathbf{R}^H \right)^*, \tag{25}$$

which can be obtained through some straightforward, albeit tedious, algebraic manipulations.

Now that all derivatives for $\mathbf{V}$ are ready from (24)-(25), we have the first-order derivative $\frac{\partial \tilde{C}}{\partial \mathbf{V}^*}$ and the Hessian matrix $\frac{\partial^2 \tilde{C}}{\partial \mathbf{V} \partial \mathbf{V}^H}$, and consequently the Newton direction as

$$\Delta \mathbf{v}_{nt} = - \left(\frac{\partial^2 \tilde{C}}{\partial \mathbf{V} \partial \mathbf{V}^H} \right)^{-1} \frac{\partial \tilde{C}}{\partial \mathbf{V}^*}. \tag{26}$$

Using the backtracking line search algorithm [10] to obtain a step size p, we update

$$\mathbf{V} \leftarrow \mathbf{V} + p \Delta \mathbf{v}_{nt}. \tag{27}$$

In summary, we update the weights of the destination and relay nodes according to (20) and (27), until the cost function (19) converges.

V. Numerical Simulations

In this section, we simulate a relay network as shown in Fig. 1 to verify the effectiveness of the proposed NAF scheme. The source-to-relay and the relay-to-destination channels are assumed to be frequency-flat Rayleigh fading and remain static in the simulated time duration. The SNRs of both channels are denoted as ρ_{relay} and ρ_{dest}, respectively. Each interference is 10dB stronger than the signal. The destination has only one receiving antenna ($M_d = 1$). The hyperbolic parameter in (6) is $c = 0.3$; the moment parameters in (15) are $\alpha = 0.3$ and $\lambda = 0.8$.

While the NAF-BP algorithm is conducted based on $T = 200$ pilot sequences, each of length $L = 100$, the benchmark scheme NAF-SCP is based on 4000 pilot samples. We use the output SINR of the destination as the performance metric [cf. (4)], based on the average of 500 Monte Carlo trials. Some parameter values not stated in the text are given on the top of the figures.

We first analyze the impact of the number of relays (N) on the performance of the NAF-BP algorithm, where all the relays have only one receiving antenna ($M_r = 1$) and are affected by two interferences ($K = 2$). Fig. 4 shows that the relay network employing the NAF-BP algorithm can suppress interference effectively after sufficient number of iterations. As expected, the performance of the algorithm improves as the number of relays increases.

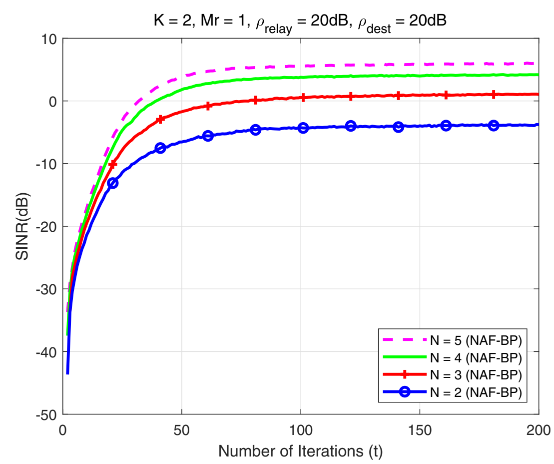

Fig. 4: Output SINR of the destination versus the number of iterations with respect to different number of relay nodes.

Fig. 5 compares the performance of the NAF-BP algorithm with the NAF-SCP scheme based on $N = 2, M_r = 2$. Since the NAF-SCP benchmark does not group sequences to train iteratively, we only draw its final converged result. Fig. 5 shows that the NAF-BP algorithm can perform nearly as good as the benchmark. Meanwhile, both algorithms can suppress up to 3 interferences via coordinating the relay nodes to perform like a virtual four-antenna relay node.

Fig. 6 simulates the relay network in absence of interference, which is based on the average of 100 channel realizations. Here we include the algorithm in [8] as it is designed to optimize the AF relay network in the interference-free scenario. Compared with [8], which only constrains the average power of the relays, our algorithms actually impose an instantaneous power constraint upon the relay nodes, which is more stringent and

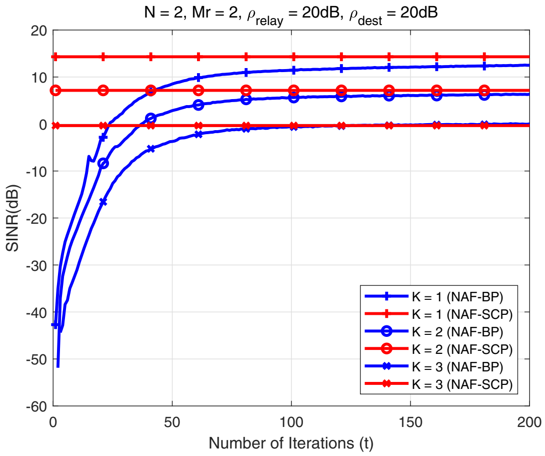

Fig. 5: Comparison of the NAF-BP and NAF-SCP algorithms in the output SINR of the destination with respect to different number of the interferences.

more realistic. Fig. 6 shows that the NAF-SCP algorithm can uniformly outperform the linear AF-based algorithm in [8], which suggests that our proposed NAF scheme may have some fundamental benefits over its linear counterpart.

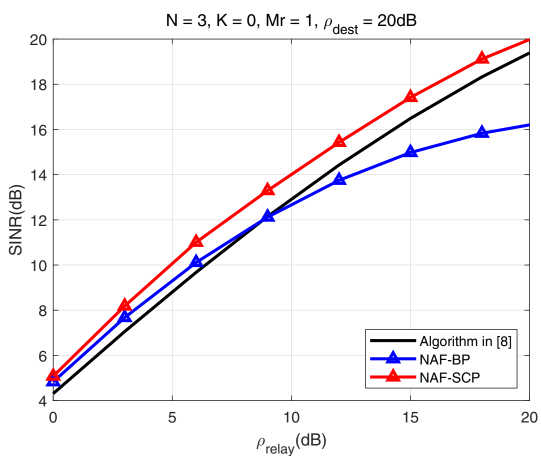

Fig. 6: Comparison between the proposed algorithms with the algorithm in [8] in the output SINR of the destination.

VI. Conclusions

We propose a novel Nonlinear Amplify-and-Forward (NAF) scheme for a relay network consisting of one source, one destination, and multiple relay nodes in the presence of interferences. We design a hyperbolic signal-amplitude-compression model for instantaneous constraint on the transmit power of each antenna of the relay nodes. By exploiting the striking similarity between a relay network and a three-layer artificial neural network, we propose a back-propagation inspired algorithm for the NAF relay scheme to optimize the weights of the destination and relay nodes. The distributed relay nodes can then achieve interference suppression with no channel state information and no data exchange between themselves. Moreover, we develop a sequential convex programming based algorithm for the NAF relay scheme as a performance benchmark. The effectiveness of the proposed NAF scheme is verified through extensive simulations in both interference and interference-free environment.

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