Transmission of analog correlated sources over MIMO fading channels

Pedro Suárez-Casal, Óscar Fresnedo, Luis Castedo
Department of Electronics and Systems
University of A Coruña, SPAIN
{pedro.scasal, oscar.fresnedo, luis}@udc.es

Javier García-Frías
Department of Electrical & Computer Engineering
University of Delaware, USA
jgf@udel.edu

***Abstract*—In this work, we address the transmission of correlated Gaussian sources over Multiple Input Multiple Output (MIMO) fading channels using analog Joint Source Channel Coding (JSCC). The source symbols are first compressed using a continuous parametric mapping based on a sinusoidal function that exploits the source correlation. Given that the data at the encoder output is also correlated, the information corresponding to the covariance matrix is incorporated into the design of the linear transmit and receive filters. The promising results obtained from the simulations confirm the suitability of analog JSCC techniques for the considered scenario.**

I. Introduction

The application of analog Joint Source Channel Coding (JSCC) techniques for the transmission of independent analog sources has been analyzed for different scenarios and communication models [1], [2], [3], [4]. These works confirm that this transmission strategy is a feasible alternative to traditional approaches based on the separation of the source and the channel coding operations. Analog JSCC has also been considered for the transmission of correlated sources, specially in the context of wireless sensor networks [5], [6], [7]. The source-channel separation is suboptimal in scenarios such as the Multiple Access Channel (MAC) when the information is correlated, since the separate optimization of the source and channel encoders is not able to efficiently exploit the source correlation [5], [8], [9]. For this reason, analog JSCC techniques are particularly appealing for these scenarios.

In this work, we address the transmission of discrete-time analog correlated symbols over fading channels using analog JSCC. The transmitter and receiver are also equipped with multiple antennas to increase the spectral efficiency. The main contributions of this work are summarized as follows:

- A parametric non-linear analog mapping is proposed to exploit the correlation of two consecutive source symbols to produce one encoded symbol (bandwidth compression). The advantage of parametric mappings with respect to non-parametric ones is the significant reduction of the computational cost in the coding and decoding operations. In addition, the utilization of parametric mappings enables the affordable optimization of the analog JSCC system by adapting the encoder parameters to the channel time variations.
- The proposed analog JSCC system for Multiple Input Multiple Output (MIMO) channels exhibits extremely low complexity and delay thanks to the system design based on a two-stage structure similar to the one proposed for uncorrelated sources in [10].
- The design of the transmit and receive linear filters incorporates the correlation information after the analog JSCC encoding. Two different methods are considered to estimate such correlation. Initially, the transformation of the source symbols is assumed to be linear and, hence, the correlation between the symbols at the encoder output can be analytically calculated. This approximation can be improved by using the unscented transform to model the covariance matrix after the non linear transformations performed by the analog encoder.
- The performance of the proposed analog JSCC system is evaluated over fading MIMO channels. Other well-known analog mappings are also considered to illustrate the suitability of the proposed mapping for this scenario. Finally, the obtained results are compared to the theoretical bounds given by the Optimum Performance Theoretically Attainable (OPTA).

In summary, we show that the utilization of parametric analog mappings allows to efficiently exploit the correlation among the source symbols. The resulting analog JSCC system is also able to achieve high transmission rates due to the compression operation at the encoder, and the use of multiple antennas at the transmitter and the receiver. An additional advantage of this approach is the simplicity for the system optimization depending on the specific channel conditions.

II. System Model

Let us assume a correlated analog source modeled as an autoregressive random process of order one, AR(1),

$$s_k = \rho s_{k-1} + e_k \tag{1}$$

where ρ is a constant parameter, and e_k is a zero-mean Gaussian distributed variable with variance $\sigma_\epsilon^2 = 1 - \rho^2$. In such model, the correlation between two arbitrary symbols is $\mathbb{E}[s_i s_{i+n}] = \rho^n$. Hence, two consecutive source symbols, $\mathbf{s}_i = [s_{2i}, s_{2i+1}]^T$, follow a bivariate Gaussian distribution with zero-mean and covariance matrix

$$\mathbf{C_s} = \mathbb{E}\left[\mathbf{s}_i \mathbf{s}_i^T\right] = \left[\begin{array}{cc} 1 & \rho \\ \rho & 1 \end{array}\right].$$

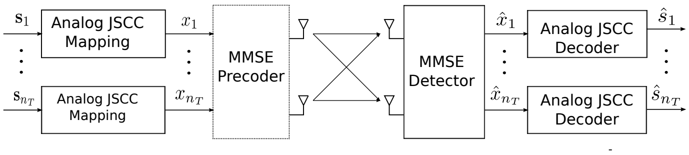

Fig. 1. Block diagram of the proposed analog JSCC system.

Figure 1 shows the block diagram of the proposed analog JSCC system for the transmission of correlated source symbols over MIMO fading channels. As shown in the figure, the transmitter and the receiver are equipped with n_T and n_R antennas, respectively. At the i-th transmit antenna, two consecutive source symbols $\mathbf{s}_i$ are encoded into one channel symbol x_i using a 2:1 analog JSCC mapping. As explained in Section IV, the analog mapping must be designed to exploit the correlation between the source symbols to be compressed.

After the encoding operation, the resulting vector of n_T symbols $\mathbf{x} = [x_1, \ldots, x_{n_T}]^T$ is precoded and sent over a MIMO fading channel. The received signal is hence given by

$$\mathbf{y} = \mathbf{HPx} + \mathbf{n}, \tag{2}$$

where $\mathbf{H}$ is the MIMO channel response matrix, $\mathbf{P}$ is the precoding matrix and $\mathbf{n}$ is the Additive White Gaussian Noise (AWGN) with $\mathbf{n} \sim \mathbb{N}_{\mathbb{C}}(0, \sigma_n^2 \mathbf{I}_{n_R})$. The precoder $\mathbf{P}$ is designed to satisfy a total transmit power constraint P_T, hence the Signal-to-Noise Rate (SNR) is $\eta = P_T/\sigma_n^2$. For simplicity, along this paper the transmit power is assumed to be $P_T = 1$.

At the receiver, the vector of n_R observed symbols is employed to calculate an estimate of the source symbols. MMSE decoding is optimum for analog JSCC given that it minimizes the distortion between source and decoded symbols. Nevertheless, the analog mapping involves non-linear transformations at the encoder and, hence, the calculation of the MMSE estimates requires the numerical computation of complex integrals.

A low-complexity alternative is the concatenation of a linear MMSE filter and a Maximum Likelihood (ML) decoder, as proposed in [10] for the analog JSCC transmission of independent sources. In such case, an MMSE linear estimate of the transmitted symbols is obtained as follows

$$\hat{\mathbf{x}} = \mathbf{Wy} = \mathbf{WHPx} + \mathbf{Wn}, \tag{3}$$

where $\mathbf{W}$ is the linear MMSE receive filter

$$\mathbf{W} = \mathbf{C}_x \mathbf{P}^H \mathbf{H}^H (\mathbf{HPC}_x \mathbf{P}^H \mathbf{H}^H + \sigma_n^2 \mathbf{I}_{n_R})^{-1}, \tag{4}$$

with $\mathbf{C}_x$ representing the covariance matrix of the encoded symbols. The covariance of the estimation error is

$$\mathbf{C}_e = \mathbf{C}_x - \mathbf{C}_x \mathbf{P}^H \mathbf{H}^H \left(\mathbf{HPC}_x \mathbf{P}^H \mathbf{H}^H + \sigma_n^2 \mathbf{I}_{n_R}\right)^{-1} \mathbf{HPC}_x. \tag{5}$$

If no Channel State Information (CSI) is available at the transmitter, the optimum precoder is $\mathbf{P}' = 1/\sqrt{n_T} \mathbf{I}_{n_T}$ and the linear MMSE detector simplifies to

$$\mathbf{W}' = (\mathbf{H}^H \mathbf{H} + n_T \sigma_n^2 \mathbf{C}_x^{-1})^{-1} \mathbf{H}^H, \tag{6}$$

An estimate of the source symbols $\hat{\mathbf{s}}_i$ is finally determined from the filtered symbols $\hat{\mathbf{x}}$ by using the corresponding ML decoder.

A. Covariance of the Encoded Symbols

The optimum transmit and receive filters should exploit the correlation of the encoded symbols to minimize the expected distortion. This correlation is determined from the covariance matrix of the source symbols $\mathbf{C}_\mathbf{s}$, and the analog JSCC mapping employed at the encoding operation.

A first estimation of the covariance matrix of the encoded symbols $\mathbf{C}_\mathbf{x}$ is obtained by approximating the non-linear analog mapping to a linear transformations $x_i = k(s_{2i} + s_{2i+1})$, where k is a factor to guarantee that $\mathbb{E}[x_i^2] = 1 \ \forall i$. For the two-antennas case, $n_T = 2$, it can be show that the covariance matrix for the encoded symbols $\mathbf{x} = [x_1, x_2]^T$ is

$$\mathbf{C}_\mathbf{x} = \mathbb{E}\left[\mathbf{x}\mathbf{x}^T\right] = \begin{bmatrix} 1 & \frac{1}{2}\rho(1+\rho) \\ \frac{1}{2}\rho(1+\rho) & 1 \end{bmatrix}.$$

In practice, we have observed that this approach provides good estimates of the actual correlation, specially in the low SNR regime where the mapping approximates a linear transform. However, these approximations could be improved by using the idea of the Unscented Transform to model the covariance after the non-linear transformations of the analog encoder.

III. Linear MMSE Precoding

Let us now consider that the CSI is available at transmission and reception. In this case, CSI knowledge can be exploited to design a linear MMSE precoder to improve the system performance.

The linear transmit and receive filters are designed to minimize the MSE between the transmitted symbols $\mathbf{x}$ and the estimates $\hat{\mathbf{x}}$. The error vector is given by

$$\mathbf{e} = \mathbf{x} - \hat{\mathbf{x}} = \mathbf{x} - \mathbf{WHPx} + \mathbf{Wn}, \tag{7}$$

and, therefore, the transmit and receive filters $\mathbf{P}$ and $\mathbf{W}$ can calculated by solving

$$\arg\min_{\mathbf{P},\mathbf{W}} \mathbb{E}\Big[\mathrm{tr}\big(\mathbf{e}\mathbf{e}^H\big)\Big] \qquad \text{s.t.} \quad \mathrm{tr}\big(\mathbf{PC}_x\mathbf{P}^H\big) = 1, \tag{8}$$

where $\mathrm{tr}(\cdot)$ represents the trace operator. This problem can be solved by differentiating this MSE expression with respect to $\mathbf{P}^H$ and $\mathbf{W}^H$. The resulting expressions can be used to obtain the filters $\mathbf{P}$ and $\mathbf{W}$ following an alternating approach.

Alternatively, a lower complexity solution can be found by following an approach similar to [11], [12] but incorporating the transmitted symbols correlation information into the derivation of the optimum filter expressions [13]. Let us consider the Single Value Decomposition (SVD) of the channel as $\mathbf{H} = \mathbf{U}_h \mathbf{\Sigma}_h \mathbf{V}_h^H$ and the SVD of the covariace matrix $\mathbf{C}_x = \mathbf{U}_x \mathbf{\Sigma}_x \mathbf{V}_x^H$. Assuming the optimum linear MMSE filters are of the form $\mathbf{P} = \mathbf{V}_h \mathbf{T} \mathbf{U}_x^H$ and $\mathbf{W} = \mathbf{U}_s \mathbf{D} \mathbf{U}_h^H$, where the matrices $\mathbf{T}$ and $\mathbf{D}$ are diagonal, the expression in (8) can be transformed in

$$\begin{aligned} \underset{\mathbf{D},\mathbf{T}}{\arg\min} \quad & \operatorname{tr}\Big(\mathbf{\Sigma}_x + \mathbf{D}\mathbf{\Sigma}_h\mathbf{T}\mathbf{\Sigma}_x\mathbf{T}^H\mathbf{\Sigma}_h^H\mathbf{D}^H \\ & \qquad + \sigma_n^2\mathbf{D}\mathbf{D}^H - 2\Re\left\{\mathbf{D}\mathbf{\Sigma}_h\mathbf{T}\mathbf{\Sigma}_x\right\}\Big) \qquad (9) \\ \text{s.t.} \quad & \operatorname{tr}\big(\mathbf{T}\mathbf{\Sigma}_x\mathbf{T}^H\big) = 1. \end{aligned}$$

Since the problem is expressed as the product of diagonal matrices, the Lagrangian cost function can be written as

$$\mathcal{L} = \sum_{i=1}^{L} \lambda_{x,i}(d_i t_i \lambda_{h,i} - 1)^2 + \sigma_n^2 d_i^2 + \Delta(\sum_{i=1}^{L} t_i^2 \lambda_{x,i} - 1), \qquad (10)$$

where d_i and t_i are the diagonal elements of $\mathbf{D}$ and $\mathbf{T}$, respectively; $\Delta \geq 0$ is a Lagrange multiplier; and $\lambda_{x,i}$ and $\lambda_{h,i}$ are the eigenvalues of the source covariance matrix and the channel, respectively. Thus, $\mathbf{\Sigma}_x = \{\lambda_{x,1}, \lambda_{x,2}, \ldots, \lambda_{x,n_T}\}$ and $\mathbf{\Sigma}_h = \{\lambda_{h,1}, \lambda_{h,2}, \ldots, \lambda_{h,L}\}$, with L the number of non-zero channel eigenvalues. The solutions for d_i and t_i are given by

$$d_i^2 = \frac{1}{\lambda_{h,i}^2}\left[\lambda_{h,i}\sqrt{\frac{\lambda_{x,i}\Delta}{\sigma_n^2}} - \Delta\right]^+ \qquad (11)$$

$$t_i^2 = \frac{1}{\lambda_{h,i}^2}\left[\lambda_{h,i}\sqrt{\frac{\sigma_n^2}{\lambda_{x,i}\Delta}} - \frac{\sigma_n^2}{\lambda_{x,i}}\right]^+, \qquad (12)$$

The operator $[\cdot]^+$ takes the positive arguments and sets negative arguments to zero.

Substituting (12) into the power constraint, the following value is obtained for the Lagrange multiplier

$$\Delta = \frac{1}{\sigma_n^2}\left(\frac{\sum_{k=1}^{L^*}\frac{\sqrt{\lambda_{x,k}}}{\lambda_{h,k}}}{\eta + \sum_{k=1}^{L^*}\frac{1}{\lambda_{h,1}^2}}\right)^2. \qquad (13)$$

Finally, substituting this value for Δ into (11) and (12), we find the following solution for the diagonal matrices $\mathbf{T}$ and $\mathbf{D}$

$$d_i = \sqrt{\frac{1}{\sigma_n^2}A_i\left[\sqrt{\lambda_{x_i}} - A_i\right]^+} \qquad (14)$$

$$t_i = \sqrt{\frac{\sigma_n^2}{\lambda_{h,i}^2}\left[\frac{1}{A_i\lambda_{x,i}} - \frac{1}{\lambda_{x_i}}\right]^+} \qquad (15)$$

where

$$A_i = \frac{\frac{1}{\lambda_{h,i}}\sum_{k=1}^{L^*}\frac{\lambda_{x,k}}{\lambda_{h,k}}}{\eta + \sum_{k=1}^{L^*}\frac{1}{\lambda_{h,k}^2}}. \qquad (16)$$

The number $L^* \leq L$ refers to the number of singular values whose corresponding expressions for d_i or t_i are non-zero. The solution previously described remembers that obtained for the case of uncorrelated inputs in [12], but including the eigenvalues of the source covariance matrix. Equivalently to [12], it can also be observed that the obtained solution resembles the traditional waterfilling algorithm in the sense that it provides the optimal distribution of the transmit power among the data streams that minimizes the MSE.

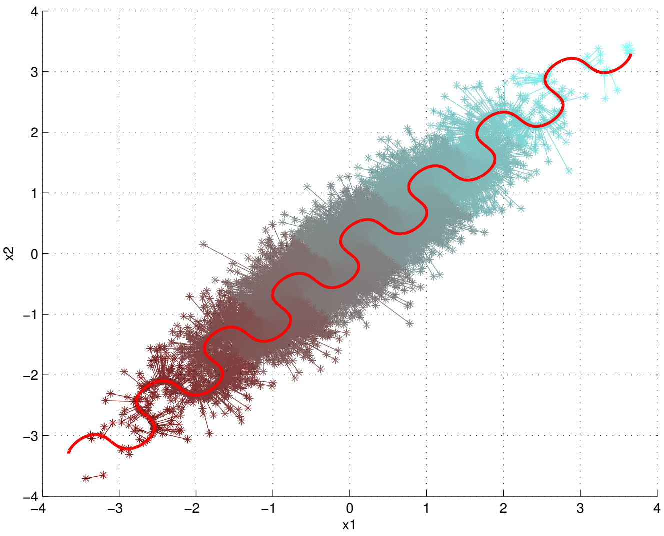

Fig. 2. Proposed 2:1 analog JSCC mapping for SNR = 25 dB.

IV. Analog JSCC Mapping

Let us focus on the 2:1 compression of the source information. A parametric non-linear analog mapping based on sinusoidal functions is proposed to transform two correlated source symbols $\mathbf{s}_i = [s_i, s_{(i+1)}]^T$ into one encoded symbol x_i. Let $\mathbf{C}_s = \mathbf{U}^H\mathbf{\Sigma}\mathbf{U}$ be the eigendecomposition of the source covariance matrix. The proposed mapping is based on the space-filling curves defined by the following parametric expression:

$$\mathbf{K}(t) = \mathbf{U}\mathbf{\Sigma}\begin{bmatrix} t - \frac{1}{2\alpha}\sin(\alpha t) \\ \Delta\sin(\alpha t) \end{bmatrix}, \qquad (17)$$

where $\mathbf{K}(t)$ represents a point into the bidimensional source space given a parameter t in the one-dimensional channel space. The parameters α and Δ represent the frequency and the amplitude of the sinusoidal function, respectively. The optimal values for these parameters specifically depend on the value of the noise variance or, equivalently, on the SNR value. An adequate optimization of α and Δ for the SNR value is important to closely approach the optimal cost-distortion tradeoff.

Besides the parametric curve given by (17), it is required to define a function $M(\mathbf{s})$ that specifies the mapping of the points in the source space into the corresponding point in the parametric curve. In this case, the mapping function is

$$x = M(\mathbf{s}) = \arg\min_t \int_{-\infty}^{\infty} \|\mathbf{s} - \mathbf{K}(u)\|^2 p_n(u-t)\mathrm{d}u, \quad (18)$$

where $p_n(n)$ represents the probability density function of the noise. If the noise distribution is disregarded, i.e., $p_n(n) = \delta(n)$, the mapping function reduces to the minimum Euclidean distance.

The utilization of this mapping is motivated by previous works for the considered scenario by using Power Constrained Channel Optimized Vector Quantizers [14] and the optimal non parametric mappings obtained by following an approach similar to [15] for the case of correlated sources.

Figure 2 shows the specific analog JSCC mapping for $\mathrm{SNR} = 25$ dB. As observed, the red curve corresponds to the sinusoidal function given by (17) with the optimal parameters α and Δ for that SNR. The point cloud around the curve is generated from a bivariate Gaussian with correlation factor $\rho = 0.9$. The figure also shows how the correlated Gaussian symbols are mapped to the corresponding point on the curve according to (18). Finally, the different colour-schemes represents the variation of the encoded values given by the curve parameter t. At the receiver, an estimate of the source symbols is computed from the observed symbols by using the Maximum Likelihood (ML) decoder which has the form $\hat{\mathbf{s}}_i = \mathbf{h}(\hat{x}_i) = \mathbf{K}(\hat{x}_i)$.

As already mentioned, the value of the parameters α and Δ can be optimized depending on the SNR to improve the system performance. In the case of fading channels, it is necessary to estimate the effective SNR at the receiver and feedback this information to the transmitter. Thereby, the encoder may adapt the mapping parameters to the channel fluctuations. The effective SNRs are estimated by using the covariance matrix of the error. Hence, the estimation of the SNRs per antenna can be obtained from (5) as

$$\hat{\boldsymbol{\eta}} = \mathrm{diag}\left(\mathbf{C}_e^{-1}\right), \tag{19}$$

where the operator $\mathrm{diag}(\cdot)$ provides a vector with the diagonal elements of the input matrix.

V. Preliminary Results

In this section, the results of computer simulations are presented to illustrate the performance of the proposed analog JSCC system for the transmission of correlated information over MIMO channels. In particular, we focus on $n_T \times n_R$ Rayleigh fading channels $\mathbf{H}$, such that $\mathbb{E}\left[\mathrm{tr}\left(\mathbf{H}\mathbf{H}^H\right)\right] = n_R n_T$. In this earlier version of the paper, we consider a 2×2 MIMO system with a correlation factor $\rho = 0.9$ for the source symbols.

The performance of analog communications is measured in terms of the Signal-to-Distortion Rate (SDR) with respect to the SNR. The SDR is defined as

$$\mathrm{SDR[dB]} = 10 \log_{10}(1/\mathrm{MSE}),$$

where the term $\mathrm{MSE} = \frac{1}{M}\sum_{i=1}^{M} \mathbb{E}\left[\|\hat{s}_i - s_i\|^2\right]$ is the MSE between the source and the estimated symbols.

It is interesting to compare the performance of an analog communication systems to the corresponding optimal cost-distortion tradeoff, referred to as the Optimum Performance Theoretically Attainable (OPTA). In general, this bound is calculated by equating the rate distortion of the source and the channel capacity [17].

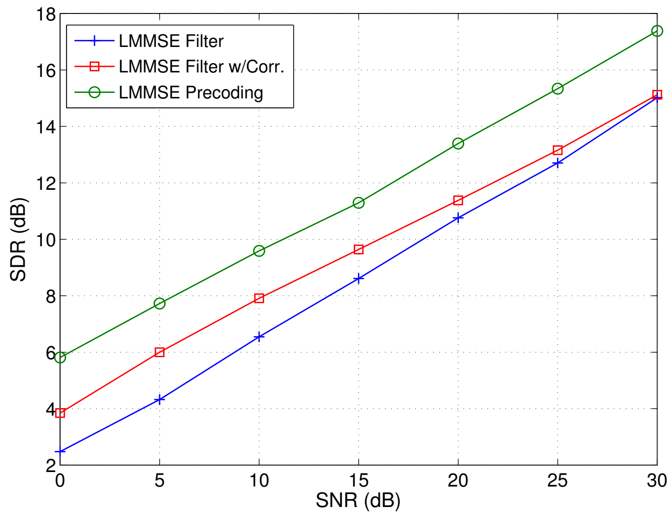

Fig. 3. Performance of the proposed analog JSCC system for 2×2 MIMO channels.

For multivariate Gaussian sources and the MSE as the distortion criterion, the rate distortion function can be represented parametrically as [18]

$$D(\theta) = \frac{1}{M}\sum_{i=1}^{M} \min[\theta, \lambda_{s,i}],$$
$$R(\theta) = \frac{1}{M}\sum_{i=1}^{M} \max\left[0, \frac{1}{2}\log\left(\frac{\lambda_{s,i}}{\theta}\right)\right], \tag{20}$$

where $D(\theta)$ is the distortion function, λ_i represent the eigenvalues of the covariance matrix and M is the source dimension. Notice that the analog JSCC system transmits $2n_T$ source symbols per channel uses, hence M is actually $2n_T$. In this case, the covariance matrix for $2n_T$ consecutive symbols generated by an AR(1) process is

$$\tilde{\mathbf{C}}_{\mathbf{s}} = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{2n_T-1} \\ \rho & 1 & \rho & \cdots & \rho^{2n_T-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{2n_T-1} & \rho^{2n_T-2} & \cdots & \rho & 1 \end{bmatrix}.$$

On the other hand, the capacity of an $n_T \times n_R$ MIMO systems is [19]

$$\mathrm{C}(\mathbf{H}) = \log\det\left(\mathbf{I}_{n_R} + \frac{1}{\sigma_n^2}\mathbf{H}\mathbf{P}\mathbf{P}^H\mathbf{H}^H\right). \tag{21}$$

Notice that the capacity given by (21) is maximized when the precoder is designed according to the waterfilling solution.

Equating (20) and (21), solving for the distortion function $D(\theta)$ and, finally, calculating the mathematical expectation of the resulting expression, we determine the expected minimum achievable distortion or, equivalently, the optimal performance depending on the considered SNR.

Figure 3 shows the performance of the analog JSCC system over 2×2 MIMO channels with a source correlation $\rho = 0.9$. The figure plots the SDR curves obtained for three different situations: 1) utilization of a linear MMSE receive filter without exploiting the correlation of the encoded symbols, 2) the receive filter exploits such a correlation, and 3) utilization of a linear MMSE precoder at transmission. As expected, the worst performance corresponds to the case of linear MMSE receive filtering for uncorrelated sources. The exploitation of the correlation into the design of the receive filters improves the system performance, specially for low and medium SNRs. In the high SNR region, the correlation factor present in (6) is less significant because it is weighted by the noise variance. In addition, the utilization of the linear MMSE precoder described in Section III significantly outperforms the two previous strategies thanks to the smart exploitation of the channel information at the transmitter.

VI. OUTLOOK

In the final version of the paper, we expect to include the following aspects:

- The generalization of the covariance matrix for n_T antennas assuming linear transformations. In addition, the Unscented Transform will be considered to estimate the covariance matrix after the non linear transformations of the analog mapping. Finally, the accuracy of the both estimates will be compared.
- The OPTA curve for this scenario, as well as a performance comparison between the proposed analog parametric mapping and other known analog JSCC mappings for the compression of Gaussian sources, such as linear or spiral-like mappings.
- A performance evaluation of the proposed communication system in other scenarios.

VII. CONCLUSIONS

In this work, we have addressed the transmission of correlated Gaussian sources over MIMO fading channels using analog JSCC. We have presented a novel parametric analog JSCC mapping to compress two source symbols into one channel symbol. In addition, the utilization of multiple antennas at both transmission and reception allows to increase the system throughput. The structured design of the proposed system preserves the main advantages of analog JSCC communications, namely, low complexity, negligible latency and robustness against time variations of fading channels. According to this idea, we have designed those linear transmit and receive filters that minimize the signal distortion considering the specific correlation at the encoded symbol vectors to be transmitted. The promising results obtained in the simulations confirm the suitability of analog JSCC techniques for the considered scenario.

REFERENCES

[1] F. Hekland, P. Floor, and T. A. Ramstad, "Shannon-Kotel'nikov mappings in joint source-channel coding," *IEEE Trans. on Communications*, vol. 57, no. 1, pp. 94–105, Jan 2009.

[2] O. Fresnedo, J. González-Coma, M. Hassanin, L. Castedo, and J. Garcia-Frias, "Evaluation of analog joint source-channel coding systems for multiple access channels," *IEEE Trans. on Communications*, vol. 63, no. 6, pp. 2312 – 2324, Jun 2015.

[3] J. Karlsson and M. Skoglund, "Optimized low-delay source-channel relay mappings," *IEEE Trans. on Communications*, vol. 58, no. 5, pp. 1397–1404, May 2010.

[4] S. Yao and M. Skoglund, "Analog network coding mappings in Gaussian multiple-access relay channels," *IEEE Trans. on Communications*, vol. 58, no. 7, pp. 1973–1983, Jul 2010.

[5] A. Lapidoth and S.Tingueley, "Sending a bivariate Gaussian over a Gaussian MAC," *IEEE Trans. on Information Theory*, vol. 56, no. 6, pp. 2714–2752, 2010.

[6] P. A. Floor, A. N. Kim, N.Wernersson, T. A. Ramstad, M. Skoglund, and I. Balasingham, "Zero-delay joint source-channel coding for a bivariate gaussian on a gaussian MAC," *IEEE Trans. on Communications*, vol. 60, no. 10, pp. 3091–3102, Oct 2012.

[7] N. Wernersson and M. Skoglund, "Nonlinear coding and estimation for correlated data in wireless sensor networks," *IEEE Trans. on Communications*, vol. 57, no. 10, pp. 2932–2939, Oct 2009.

[8] M. Gastpar, B. Rimoldi, and M. Vetterli, "To code, or not to code: Lossy source–channel communication revisited," *IEEE Trans. on Information Theory*, vol. 49, no. 5, pp. 1147–1158, May 2003.

[9] I. E. Aguerri and D. Guenduez, "Linear transmission of correlated Gaussian sources over MIMO channels," in *Proceedings of the 10th International Symposium on Wireless Communication Systems (ISWCS 2013)*, Aug 2013.

[10] O. Fresnedo, F. Vazquez-Araujo, L. Castedo, and J. Garcia-Frias, "Low-complexity near-optimal decoding for analog joint source channel coding using space-filling curves," *IEEE Communications Letters*, vol. 17, no. 4, pp. 745–748, Apr 2013.

[11] S.Serbetli and A. Yener, "Transceiver optimization for multiuser mimo systems," *IEEE Trans. on Signal Processing*, vol. 52, no. 1, pp. 214–226, Jan 2004.

[12] M. Rupp, O. Fresnedo, and L. Castedo Ribas, "Explicit MMSE MIMO transceiver solution for analog joint source channel coding," in *Proceeding of the 11th International Symposium on Wireless Communications Systems (ISWCS 2014), Barcelona*, Aug 2014.

[13] K.-H. Lee and D. Petersen, "Optimal Linear Coding for Vector Channels," *IEEE Transactions on Communications*, vol. 24, no. 12, pp. 1283–1290, Dec 1976.

[14] B. Lu and J. Garcia-Frias, "Non-linear bandwidth reduction schemes for transmission of multivariate Gaussian sources over noisy channels," in *Information Sciences and Systems (CISS), 46th Annual Conference on*, March 2012.

[15] E. Akyol, K. Rose, and T. Ramstad, "Optimal mappings for joint source channel coding," in *IEEE Information Theory Workshop (ITW 2010, Cairo)*, Jan 2010.

[16] S. M. Kay, *Fundamentals of Statistical Signal Processing*. Prentice Hall, 1993.

[17] T. Berger and D. Tufts, "Optimum pulse amplitude modulation–I: transmitter-receiver design and bounds from information theory," *IEEE Transactions on Information Theory*, vol. 13, no. 2, pp. 196 – 208, Apr 1967.

[18] T. Berger, *Rate Distortion Theory: A Mathematical Basis for Data Compression*. Englewood Cliffs, 1971.

[19] I. E. Telatar, "Capacity of multi-antenna gaussian channels," *Bell Labs Technical Memorandum*, Jun 1995.