BLIND SYMBOL DETECTION AND CHANNEL ACQUISITION IN FAST-FADING WIRELESS SYSTEMS WITH SPACE DIVERSITY

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ABSTRACT

In this paper we tackle the joint source symbol detection and multi-channel acquisition problem in the context of wireless digital flat-fading links with space diversity. We propose a simple parametric statistical channel model which decouples the time dynamics of the channel vector in amplitude and direction. We implement the corresponding maximum a posterior (MAP) joint estimator for the amplitude and direction of the channel vector and the source information symbols. We derive a computationally attractive iterative scheme to solve the optimization problem associated with the MAP estimator. This scheme is based on differential-geometric concepts and fully exploits the curvature of the surface constraint. Preliminary computer simulations assessing the good performance of our proposed solutions are included.

1. INTRODUCTION

Figure 1 illustrates the scenario considered herein. In figure 1,

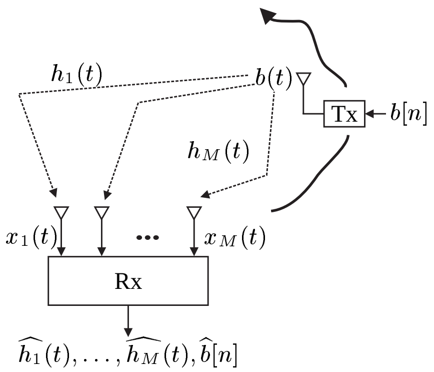

Fig. 1. Flat-fading multi-channel driven by a mobile binary source (baseband model)

$b[n]$ denotes the discrete-time sequence of transmitted information symbols, while $b(t)$ represents the continuous-time baseband signal emitted by the mobile source. The signal $h_m(t)$ represents the complex channel established between the source and the m-th receiver, and $x_m(t)$ is the observed baseband signal at the m-th receiver. Finally $\widehat{h_m}(t)$ and $\widehat{b}[n]$ denote the estimates of $h_m(t)$ and $b[n]$, respectively. We assume all activated spatial channels to be flat-fading. Moreover, the m-th receiver is time-synchronized to the transmitted signal at the symbol level. Given these assumptions, the baseband signal available at the m-th antenna can be written as

$$x_m(t) = h_m(t)\, b(t) + w_m(t),$$

where $h_m(t) = c_m(t)e^{j\theta_m(t)}$. Here, $c_m(t)$ denotes the activated spatial channel (complex-valued), while $\theta_m(t)$ models carrier phase drifts between the source and the mth antenna of the receiver. Each antenna adds zero mean complex Gaussian noise (AWGN) $w_m(t)$ with power spectral density of $2N_0$ Watts/Hz. That is, $\mathrm{E}\{w_m(t)w_m(t-\tau)^*\} = 2N_0\delta(\tau)$. Because we are interested in acquiring fast-changing channels each symbol period is oversampled by a factor P. Let each one of the received baseband signals $x_m(t)$ be oversampled by an integrate-and-dump (I&D) circuit. We have the equivalent discrete-time data model $x_m[k] = h_m[k]\, b[\lceil k/P \rceil] + w_m[k]$. Here, $\lceil a \rceil$ stands for the lowest integer greater than or equal to a. For further details on this data model see, e.g., [3]. The data model can be written in a vector format as $\boldsymbol{x}[k] = \boldsymbol{h}[k]\, b[\lceil k/P \rceil] + \boldsymbol{w}[k]$, where $\boldsymbol{x}[k] = (x_1[k], \ldots, x_M[k])^T$, and $\boldsymbol{h}[k]$ and $\boldsymbol{w}[k]$ follow similar definitions. Let N denote the number of observed symbol periods. Collect the vectors $\boldsymbol{x}[k]$, $\boldsymbol{h}[k]$ and $\boldsymbol{w}[k]$ for $k = 1, 2, \ldots, K = NP$ into the matrices $\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x}[1] & \boldsymbol{x}[2] & \cdots & \boldsymbol{x}[K] \end{bmatrix}$, $\boldsymbol{H} = \begin{bmatrix} \boldsymbol{h}[1] & \boldsymbol{h}[2] & \cdots & \boldsymbol{h}[K] \end{bmatrix}$, and $\boldsymbol{W} = [\, \boldsymbol{w}[1]\, \boldsymbol{w}[2] \cdots \boldsymbol{w}[K]\,]$. We have the matricial data model $\boldsymbol{X} = \boldsymbol{H}\, \mathrm{diag}\,(\boldsymbol{b} \otimes \boldsymbol{1}_P) + \boldsymbol{W}$. Here, $\boldsymbol{b} = (b[1], b[2], \ldots, b[N])^T$ denotes the transmitted sequence of N information symbols. The symbol $\otimes$ stands for the Kronecker product, $\mathrm{diag}(\boldsymbol{v})$ denotes a diagonal matrix with $v_1, \ldots, v_n$ as its main diagonal entries and $\boldsymbol{1}_n = (1, 1, \ldots, 1)^T$ represents the n-dimensional column vector with all entries equal to 1. We assume that the additive noise processes are spatially white, that is, $\mathrm{E}\left\{\boldsymbol{w}[k]\boldsymbol{w}[k-l]^H\right\} = \sigma^2/2\boldsymbol{I}_M\delta[l]$, where $\sigma^2 = 4N_0/\Delta$, $(\cdot)^H$ denotes the Hermitean operator (transpose conjugate) and $\delta[l]$ stands for the discrete-time Kronecker signal ($\delta[0] = 1$ and $\delta[l] = 0$ for $l \neq 0$). The matrix $\boldsymbol{I}_n$ is the $n \times n$ identity matrix.

Problem Statement. In this paper, we face the joint detection of the emitted information sequence $\boldsymbol{b}$ and estimation of the channel trajectory $\boldsymbol{H}$, given the observation matrix $\boldsymbol{X}$. We work under a Bayesian framework. We assign non-informative probabilistic priors to the channel motion $\boldsymbol{H}$ and to the transmitted data $\boldsymbol{b}$. We show that the implementation of the corresponding MAP estimator is amenable to an attractive iterative algorithm which exploits the differential geometry of the constraint surface.

Paper Organization. Section 2 motivates the chosen priors on the channel vector trajectory and source symbols. Using these priors, we implement the joint maximum a posterior (MAP) estimator for the amplitude and direction of the channel vector and the source symbols. In section 3, we discuss how to implement

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the MAP estimator. We fix the discrete variables $\boldsymbol{b}$ and solve a subproblem for the channel parameters, over all possible combinations of $\boldsymbol{b}$. We use a second-order geodesic descent method to solve each subproblem. Section 4 presents some preliminary computer simulations. Section 5 concludes our paper.

2. CHANNEL AND SOURCE PROBABILISTIC PRIORS

The purpose of this section is to motivate the choices of the statistical models for the channel/source pair. We start by reviewing some standard models for the fading channel $c_m(t)$ in terms of its first and second-order statistics for some idealized scenarios.This material is taken mostly from [3] and [4]. For example, consider a rich scattering environment. Many (high number) of different propagation paths are established between the source and the receiver. By invoking the central limit theorem, $c_m(t)$ can be modelled as a wide-sense stationary (WSS) Gaussian process, see [4]. If there exists a direct line-of-sight (LOS) between the antennas, the Rice fading model can be adopted. Otherwise, $c_m(t)$ can be taken as zero-mean and the use of the Rayleigh fading model is the adequate choice. Outside the Gaussian context, other models frequently adopted for the distribution of the amplitude of the channel $|c_m(t)|$ are the Nakagami-q (Hoyt), the Nakagami-n, and the Nakagami-m, see [3]. With respect to second order statistics, it can be shown that, in the idealized scenario where the scatterers are uniformly distributed in angle, the receiving antenna is omnidirectional and the mobile speed is constant, we have the well-known Clarke's model, see [3, 4]. In that case, the autocorrelation function of the channel is given by $r_m(\tau) = \mathrm{E}\left\{c_m(t)c_m(t-\tau)^*\right\} = \sigma_m^2 J_0\left(2\pi f_m \tau\right)$. Here, $\sigma_m^2 = \mathrm{E}\left\{|c_m(t)|^2\right\}$ denotes the power of the fading channel, $J_0(\cdot)$ is the zero-order Bessel function of the first kind, and f_m is the maximum Doppler frequency in Hz.

In scenarios where the receiver is equipped with several antennas, the amplitude of the channel vector $\rho(t) = \|\boldsymbol{h}(t)\|$ tends to change slowly when compared to the direction of the same vector $\boldsymbol{u}(t) = \boldsymbol{h}(t)/\|\boldsymbol{h}(t)\|$, see, e.g., [5]. If the autocorrelation function of each activated spatial channel is given by the Clarke's model it is possible to confirm this property through simulations for time intervals corresponding to a small number of symbol periods, see [6]. Throughout this paper, we only process small blocks of data. This precludes the usage of second order statistics methods [1, 2]. The qualitatively asymmetric behavior of $\rho(t)$ and $\boldsymbol{u}(t)$ becomes more noticeable if more statistically independent antennas are deployed at the receiver (spatial diversity), or if a Rice channel model is considered, as both of these scenarios tend to stabilize the amplitude of the channel vector. In fact, this property is a generalization of the typical behavior of single-channel systems. Notice that, for $M = 1$ channel given by $h(t) = A(t)e^{j\phi(t)}$, we have $\rho(t) = A(t) \geq 0$, and the vector $\boldsymbol{u}(t)$ specializes to the pure (unit-amplitude) phasor $\boldsymbol{u}(t) = e^{j\phi(t)}$, where $\phi(t)$ accounts for the joint time variation of the phase of the fading channel and the carrier phase drift. This behavior of $\rho(t)$ and $\boldsymbol{u}(t)$ suggests the decoupling of the time dynamics of $\boldsymbol{h}(t)$ in amplitude and direction. In terms of discrete time data, $\boldsymbol{h}[k] = \rho[k]\boldsymbol{u}[k]$, where $\rho[k] \geq 0$ and $\|\boldsymbol{u}[k]\| = 1$. For simplicity, we assume that the amplitude of the channel vector is constant, $\rho[k] = \rho$ for $k = 1, 2, \ldots, K$. We take the random variable ρ uniformly distributed over the interval $[0, A]$, where $A > 0$ is a fixed constant $\rho \sim \mathcal{U}\left([0, A]\right)$. This distribution acts as a non-informative prior on ρ. The sequence $\{\boldsymbol{u}[1], \boldsymbol{u}[2], \ldots, \boldsymbol{u}[K]\}$ is statistically independent of ρ and is taken to be a first-order Markov process on the unit-sphere. More specifically, let

$$\boldsymbol{v}[k] = \left(\mathrm{Re}\,\boldsymbol{u}[k]^T \; \mathrm{Im}\,\boldsymbol{u}[k]^T\right)^T. \tag{1}$$

Notice that each $2M$-dimensional vector $\boldsymbol{v}[k]$ lies in $\mathbb{S}^{2M-1}$. Here, and for further reference, $\mathbb{S}^{n-1} = \{\boldsymbol{v} \in \mathbb{R}^n : \|\boldsymbol{v}\| = 1\}$ denotes the $(n-1)$-dimensional unit-sphere in the Euclidean space $\mathbb{R}^n$. We let $\boldsymbol{v}[1]$ be uniformly distributed over the sphere $\mathbb{S}^{2M-1}$, written

$$\boldsymbol{v}[1] \sim \mathcal{U}\left(\mathbb{S}^{2M-1}\right), \tag{2}$$

and let the one-step transition probability be given by

$$\boldsymbol{v}[k] \,|\, \boldsymbol{v}[k-1] \sim \mathcal{M}_{2M}\left(\boldsymbol{v}[k-1], \kappa\right). \tag{3}$$

Here, $\mathcal{M}_p\left(\boldsymbol{\mu}, \kappa\right)$ denotes the von Mises-Fisher distribution on $\mathbb{S}^{p-1}$ with the unit-norm vector $\boldsymbol{\mu}$ as mean direction and the non-negative scalar κ as the concentration parameter, see [7]. The density of the von Mises-Fisher distribution $\mathcal{M}_p\left(\boldsymbol{\mu}, \kappa\right)$ with respect to the uniform distribution on the unit-sphere is

$$f\left(\boldsymbol{v}\right) = \alpha_p(\kappa)\, \exp\left(\kappa\, \boldsymbol{\mu}^T \boldsymbol{v}\right), \tag{4}$$

where $\boldsymbol{v} \in \mathbb{S}^{p-1}$ and $\alpha_p(\kappa)$ denotes the normalizing constant. This distribution reduces to the uniform distribution on the unit-sphere for $\kappa = 0$, and exhibits a mode at $\boldsymbol{\mu}$ for $\kappa > 0$. As κ increases, the probability mass becomes more concentrated around the mean direction $\boldsymbol{\mu}$ (in our context, the channel becomes slower). The uniform density assumption $\boldsymbol{v}[1] \sim \mathcal{U}\left(\mathbb{S}^{2M-1}\right)$ about the initial direction vector is adopted to reflect our ignorance about the initial vector channel state (non-informative prior). The von Mises-Fisher model for the one-step transition probability can also be seen as a non-informative prior because it doesn't imply any major constraints in the trajectory of $\boldsymbol{v}[k]$. In fact, the first-order Markov probabilistic structure of $\boldsymbol{v}[k]$ is only trying to model the continuity of the corresponding continuous-time signal $\boldsymbol{v}(t)$. It is both interesting and elucidative to notice that this model can also be obtained by relaxing the model corresponding to M point-to-point links. Let $h_m[k-1], h_m[k] \in \mathbb{C}$ denote two consecutive samples of the channel established between the source and m-th antenna of the receiver. Decouple them in amplitude and phase $h_m[k-1] = A_m[k-1]e^{j\phi_m[k-1]}$ and $h_m[k] = A_m[k]e^{j\phi_m[k]}$. Assuming a constant amplitude: $h_m[k] = e^{j\Delta_m[k]}h_m[k-1]$, where $\Delta_m[k]$ is the phase shift between the realizations of the channel. Defining the vector $\widetilde{v}_m[k] = \left(\mathrm{Re}\,u_m[k]^T \; \mathrm{Im}\,u_m[k]^T\right)^T$, we have

$$\widetilde{v}_m[k] = \underbrace{\begin{bmatrix} \cos\left(\Delta_m[k]\right) & -\sin\left(\Delta_m[k]\right) \\ \sin\left(\Delta_m[k]\right) & \cos\left(\Delta_m[k]\right) \end{bmatrix}}_{\boldsymbol{\Delta}_m[k]} \widetilde{v}_m[k-1]. \tag{5}$$

Consider now the M antennas at the receiver

$$\widetilde{\boldsymbol{v}}[k] = \begin{bmatrix} \widetilde{\boldsymbol{v}}_1[k] \\ \vdots \\ \widetilde{\boldsymbol{v}}_M[k] \end{bmatrix} = \begin{bmatrix} \mathrm{Re}\,u_1[k] \\ \mathrm{Im}\,u_1[k] \\ \vdots \\ \mathrm{Re}\,u_M[k] \\ \mathrm{Im}\,u_M[k] \end{bmatrix}. \tag{6}$$

The transition model is $\widetilde{\boldsymbol{v}}[k] = \boldsymbol{\Delta}[k]\,\widetilde{\boldsymbol{v}}[k-1]$, where $\boldsymbol{\Delta}[k] = \operatorname{diag}(\boldsymbol{\Delta}_1[k], \ldots, \boldsymbol{\Delta}_M[k])$ with each $\boldsymbol{\Delta}_m[k]$ defined as in (5). Notice that the vector $\widetilde{\boldsymbol{v}}[k]$ in (6) is equal to $\boldsymbol{v}[k]$ in (1) apart a permutation. The model can be written as $\boldsymbol{v}[k] = \boldsymbol{\Gamma}[k]\,\boldsymbol{v}[k-1]$ where

$$\boldsymbol{\Gamma}[k] = \begin{bmatrix} \boldsymbol{C}[k] & -\boldsymbol{S}[k] \\ \boldsymbol{S}[k] & \boldsymbol{C}[k] \end{bmatrix}.$$

Here, $\boldsymbol{C}[k] = \operatorname{diag}(\cos(\Delta_1[k]), \ldots, \cos(\Delta_M[k]))$ and $\boldsymbol{S}[k] = \operatorname{diag}(\sin(\Delta_1[k]), \ldots, \sin(\Delta_M[k]))$. Thus, $\boldsymbol{v}[k]$ is obtained by applying a structured perturbation to $\boldsymbol{v}[k-1]$. That is, for a given $\boldsymbol{v}[k-1]$ not all the points in the sphere $\mathbb{S}^{2M-1}$ are possible realizations for $\boldsymbol{v}[k]$. On the other hand, with the von Mises-Fisher model $\boldsymbol{v}[k]$ is obtained by applying a random unstructured perturbation to $\boldsymbol{v}[k-1]$. This is the previously mentioned model relaxation. Remark that our channel statistical model is a 1-parameter model (κ) that does not rely on any special assumption about the scattering environment, antenna directivity pattern, etc. Its main purpose is to be able of reproducing the typical time variation of the channel vector $\boldsymbol{h}(t)$ over small observation intervals, which occurs in many flat-fading propagation scenarios. Regarding the transmitter model, we consider that the information source emits a string $\{b[n]\}$ of independent and identically distributed symbols drawn from a finite modulation alphabet. For simplicity, we assume hereafter a binary-shift keying (BSK) digital source, i.e., the symbols $b[n]$ are taken from the alphabet $\{-1, 1\}$ and are equiprobable (non-informative prior).

3. MAP CHANNEL AND SYMBOL ESTIMATORS

The MAP estimates of the random objects $\boldsymbol{V} = [\,\boldsymbol{v}[1] \cdots \boldsymbol{v}[K]\,]$, ρ and $\boldsymbol{b}$ correspond to the global solutions of the optimization problem

$$\left(\widehat{\rho}, \widehat{\boldsymbol{V}}, \widehat{\boldsymbol{b}}\right) = \underset{\rho, \boldsymbol{V}, \boldsymbol{b}}{\arg\max}\ p\left(\rho, \boldsymbol{V}, \boldsymbol{b} \,|\, \boldsymbol{X}\right).$$

Notice that, due to the adopted priors, we have the following constraints: $0 \leq \rho \leq A$, $\|\boldsymbol{v}[k]\| = 1$ for $k = 1, 2, \ldots, K$ and $b[n] \in \{\pm 1\}$ for $n = 1, 2, \ldots, N$. We are assuming that both the noise variance σ^2 and the concentration parameter κ are known. Using the Bayes rule and our statistical assumptions, we have, after some trivial algebraic manipulations, the equivalent optimization problem

$$\left(\widehat{\rho}, \widehat{\boldsymbol{V}}, \widehat{\boldsymbol{b}}\right) = \underset{\rho, \boldsymbol{V}, \boldsymbol{b}}{\arg\min}\ \psi\left(\rho, \boldsymbol{V}, \boldsymbol{b}\right) \tag{7}$$

where

$$\psi\left(\rho, \boldsymbol{V}, \boldsymbol{b}\right) = \rho^2 - \frac{2}{K}\sum_{k=1}^{K} \rho\, \boldsymbol{y}_{\boldsymbol{b}}[k]^T \boldsymbol{v}[k] - \frac{\sigma^2 \kappa}{2K}\sum_{k=2}^{K} \boldsymbol{v}[k]^T \boldsymbol{v}[k-1],$$

and $\boldsymbol{y}_{\boldsymbol{b}}[k] = \left(b[\lceil k/P \rceil]\,\operatorname{Re}\boldsymbol{x}[k]^T b[\lceil k/P \rceil]\,\operatorname{Im}\boldsymbol{x}[k]^T\right)^T$ for $k = 1, 2, \ldots, K$. The optimization problem in (7) is posed in terms of a set of discrete ($\boldsymbol{b}$) and continuous ($\rho, \boldsymbol{V}$) variables. It may be solved by enumerating all bit sequences of length N and, for each one, say $\boldsymbol{b}$, optimize over ρ and $\boldsymbol{V}$ to yield the corresponding estimates $\rho_{\boldsymbol{b}}$ and $\boldsymbol{V}_{\boldsymbol{b}}$,

$$\left(\rho_{\boldsymbol{b}}, \boldsymbol{V}_{\boldsymbol{b}}\right) = \underset{\rho, \boldsymbol{V}}{\arg\min}\ \psi\left(\rho, \boldsymbol{V}, \boldsymbol{b}\right). \tag{8}$$

In fact, since there is an unavoidable sign ambiguity in the variables $\boldsymbol{V}$ and $\boldsymbol{b}$, because $\psi\left(\rho, \boldsymbol{V}, \boldsymbol{b}\right) = \psi\left(\rho, -\boldsymbol{V}, -\boldsymbol{b}\right)$, we may fix a bit, e.g., $b[1] = -1$, and enumerate over all 2^{N-1} bit sequences $\{b[2], \ldots, b[N]\}$ solving, for each one, the optimization problem in (8). This approach may be implemented through a bank of 2^{N-1} parallel processors, which is feasible for small sequence lengths N (as we are assuming throughout the paper). Each processor solves problem (8) for a fixed sequence of bits $\boldsymbol{b}$. To solve problem (8), we use a second order geodesic descent method. The theory behind this method is inspired in the differential-geometric viewpoint taken in [8] for efficiently solving certain constrained optimization problems. The general idea is as follows: fixing $\boldsymbol{V}$ solve a simple quadratic problem over ρ; then, fixing ρ and using $\boldsymbol{V}$ from the previous iteration, compute the Newton direction $\boldsymbol{d}_N$; verify if $\boldsymbol{d}_N$ is a descent direction; if so, use $\boldsymbol{d}_N$ and $\boldsymbol{V}$ to compute the geodesic $\boldsymbol{\gamma}(t)$ which starts from $\boldsymbol{V}$ in the direction $\boldsymbol{d}_N$, otherwise instead of using $\boldsymbol{d}_N$ use $\boldsymbol{d}_{SD}$ (steepest descent direction) in the calculation of the geodesic; in either case, obtain the new $\boldsymbol{V}$ using the Armijo rule. Notice that, geometrically, optimizing over $\boldsymbol{V}$ (with ρ fixed) corresponds to searching over a high-dimensional torus (the constraint surface). In the general case, computing the Newton direction would require $\mathcal{O}\left(\frac{1}{3}[(2M-1)K]^3\right)$ flops, but it can be shown that, by using the special structure of this problem, we only need $\mathcal{O}\left(3K(2M-1)^3 + 4K(2M-1)^2\right)$ flops. This fact makes the use of Newton steps bearable from the computational viewpoint. Details are omitted due to paper length restrictions, see [5].

4. PRELIMINARY COMPUTER SIMULATIONS

In this section, we present some preliminary computer simulations to assess the performance of our proposed solutions. Further results can be found in [5]. We start by considering a $M = 1$ antenna receiver. We assumed an oversampling factor of $P = 3$ and process $N = 4$ consecutive bits. Thus, the data packet length is $K = PN = 12$. Each data packet is generated according to our channel and source priors. We have fixed the vector channel amplitude throughout the simulations, $\rho = 1$ (ignored at the receiver) and considered as von Mises-Fisher concentration parameters $\kappa = 5, 10, 20$. For each κ, we varied the signal-to-noise ratio (SNR) from $\mathrm{SNR}_{\min} = -5$ dB to $\mathrm{SNR}_{\max} = 20$ dB in steps of $\Delta = 2.5$ dB, where $\mathrm{SNR} = \mathrm{E}\left\{\|\boldsymbol{h}[k]b[k]\|^2\right\} / \mathrm{E}\left\{\|\boldsymbol{w}[k]\|^2\right\} = 2/\sigma^2$. For each SNR, 2000 statistically independent Monte-Carlos runs are performed. For this set of preliminary simulations, we also assume that the sequence of bits $\boldsymbol{b}$ is known. Thus, we only face the task of estimating the channel. In equivalent words, we must solve (8) for a given (training) sequence of bits $\boldsymbol{b}$. Our method requires an initialization point $\boldsymbol{V}_0$. In these simulations, we let $\boldsymbol{V}_0$ denote the true value of $\boldsymbol{V}$ perturbed with a random disturbance. The amplitude of this random disturbance is obtained using results from [6]. In [6] the optimization problem in (8) is reformulated into a nearby semidefinite programming (SDP). The algorithm that we describe in this paper can be used to refine the results obtained in [6]. In figure 2, we plot the mean of the estimate $\widehat{\rho}$ versus SNR. As can be seen, the estimate converges to the true value $\rho = 1$, as the SNR tends to infinity. Since $M = 1$, each channel direction $\boldsymbol{u}[k]$ is a point in the unit-radius circle of the complex plane. In figure 3, we show the average absolute phase error obtained by our estimator. Notice that with our von Mises-Fisher channel model, the phase of the channel has a mean jump of $22.2, 15.8$ and 11.8 degrees from $\boldsymbol{u}[k]$ to $\boldsymbol{u}[k+1]$ (separated in time by one third of

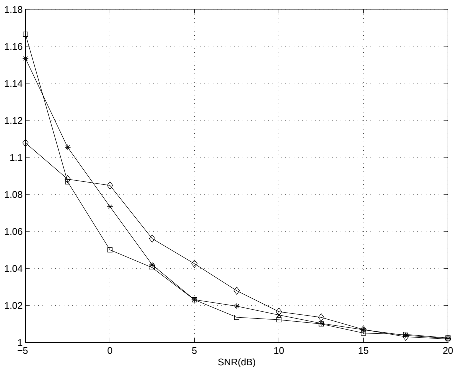

Fig. 2. Estimated fading amplitude ($\widehat{\rho}$) versus SNR ($\Box - \kappa = 20, * - \kappa = 10$ and $\Diamond - \kappa = 5$)

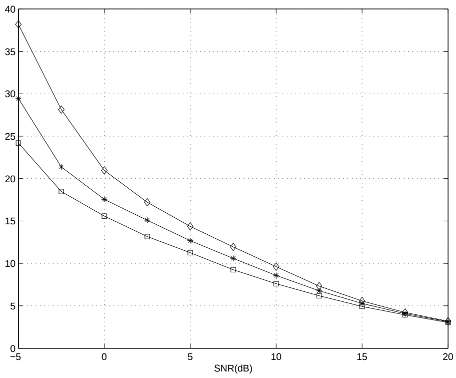

Fig. 3. Mean phase error (degrees) versus SNR ($\Box - \kappa = 20, * - \kappa = 10$ and $\Diamond - \kappa = 5$)

the symbol period), for $\kappa = 5, 10$ and 20, respectively. Thus, we are tackling a scenario with rapid channel phase variation. In order to test the robustness of our overall approach in the face of other channel models, we generate the observation matrix $\boldsymbol{X}$ using the Clarke's model. We consider an $M = 3$ antenna array receiver which observes a digital source with a symbol period of 0.1 ms, and a carrier frequency equal to 1 GHz. Moreover, we assume that source moves with a speed of 120 Km/h, and that the crystal oscillator at the receiver has a stability of 0.5 ppm. With this model the mean jump of the direction of the channel vector, from one sample to the next, is 1.82 degrees. Because of this fact we use $\kappa = 30$ as our von Mises-Fisher concentration parameter. The remaining simulation parameters are maintained and 2000 Monte-Carlo runs are performed per simulated SNR. In figure 4, we show the average absolute difference in degrees between the estimate and the true value of the direction of the channel vector. The outcome of this last block of simulations suggest that our method is well adapted to other channel models although further simulations are required to reach more conclusive statements, see [5].

5. CONCLUSIONS

We addressed the problem of joint source symbol detection and multi-channel estimation in the context of flat-fading wireless communications. We rely on a simple vector channel model which, however, captures the typical channel behavior of many flat-fading

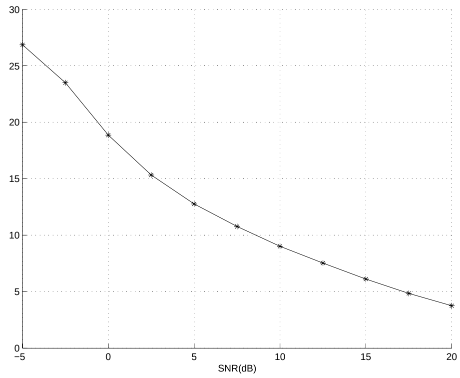

Fig. 4. Mean difference between the estimate and the true value of the direction of the channel vector (degrees) versus SNR

propagation scenarios. We decouple the time dynamics of the multi-channel vector in amplitude and direction over short time intervals. We let the amplitude remain constant and model the time variation of the channel direction as a first-order Markov walk on the unit-sphere. We implemented the corresponding MAP estimator of the emitted symbol sequence and channel realization. We derived a low-cost computational iterative scheme, based on differential-geometric concepts, to solve the optimization problem associated with the MAP estimator. Preliminary results assessed the ability of our method in acquiring fast-changing channels. These results also suggested that our approach is robust enough to handle standard channel models.

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