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Data detection in relay-based communication systems using Bayesian methods

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ABSTRACT

Data detection in a relay-based communication system (RCS) is challenging because its end-to-end channel, which comprises a cascade of several channels, has unique statistical characteristics. Assuming different channel conditions, in this paper, we address the problem of data detection in an RCS where one amplify-and-forward relay is used as an intermediate node between a transmitter and a receiver. Our approach is based on Bayesian methodologies in which a variant of Markov Chain Monte Carlo (MCMC) technique, known as Metropolis–Hasting-within-Gibbs, is applied for systems with quasi-static channel models, whereas particle filtering technique is used for systems with fast varying channels to develop joint data detection and channel estimation algorithms. By providing detailed derivations, we present two algorithms for each channel condition by formulating the transmission process of the communication systems in different ways. The effectiveness of our algorithms is demonstrated through computer simulations.

1. Introduction

In the last two decades, pervasive availability of powerful computers has spurred interest in applying simulation-based Bayesian methods to many signal processing problems arising in various disciplines including the field of communications. Particularly, Markov Chain Monte Carlo (MCMC) methods [1,2] and particle filtering techniques have been extensively and successfully used in solving various communication problems [3]. Some of the problems that have been addressed by the Bayesian methods include channel estimation [4,5], equalization [6,7], synchronization [8], and data detection in single-antenna and in multiple-antenna systems [9] in both single-user and multi-user environments [10]. In this paper, we extend the application of these methods to data detection and channel estimation for a relay-based communication system (RCS).

In an effort to improve the performance of traditional cellular communication systems, recently there has been an interest in the development of relay-based communication networks which consist of relays acting as intermediate nodes between transmitters and receivers. A potential benefit of RCSs is increasing the capacity and coverage of communication networks [11,12] without the cost of setting up new base stations (BSs) and their accompanying infra-structure. In the traditional cellular networks, a need for increasing capacity in a specific area is commonly met by splitting a cell into smaller sizes and setting up new base stations. However, setting up a new BS has its limitations. In dense urban areas, the cell sizes become increasingly small and finding locations for setting up new BSs becomes difficult. Moreover, the cost of a BS and its accompanying infrastructure is much higher than the cost of a relay. Because of its improved performance and cost effectiveness, therefore, a relay-based communication network is presented as an alternative to expand cellular coverage. As a result of these promising potential benefits, recently a lot of research effort has been directed at the study of RCS, including modeling relay-channels [13] and development of data detection and channel estimation algorithms [14,15].

An RCS comprises a cascade of several channels that include transmitter-to-relay, relay-to-relay, and relay-to-receiver channels. The overall effective channel of an RCS has, therefore, a different characteristics from that of the channel of the traditional transmitter-to-receiver cellular transmission. Especially, in a system where the relay and the receiver are mobile, the overall channel has faster time variation than the channel of a point-to-point communication system. Moreover, due to the multiplication effect of the fading process of the cascaded channels, the overall channel has a different probabilistic model than the commonly used Rayleigh fading process for non-line-of-sight (NLoS) cellular network. Therefore, these unique channel characteristics make data detection in RCS more challenging than in a point-to-point communication system.

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Several research works on data detection for RCS have been reported in the literature. The most common approaches are Least Square (LS) or Linear Minimum Mean Square Error (LMMSE) Estimation methods [13]. These methods use pilot signals for channel estimation to achieve a reasonable symbol-error rate. However, the pilot signals, especially in RCSs where the channels rapidly vary, take up a significant proportion of the transmitted data, and, as a result, such methods waste a lot of bandwidth. Other approaches for data detection in RCSs apply extended Kalman filtering [13] by approximating, through linearization, of the signal model. Furthermore, Bayesian methods that use particle filtering techniques have also been reported in [16] and in our work [14,15].

In this paper, we deal with the problem of data detection in a single-hop RCS where there is one Amplify-and-Forward (AF) relay between a transmitter and a receiver. Following the Bayesian approach, we develop joint data detection and channel estimation algorithms for different channel conditions, i.e., for time-varying and quasi-static channel models.

We assume that the quasi-static channels remain constant for a duration of one frame but vary randomly across frames. For such channels, we develop data detection and channel estimations algorithms based on a variant of MCMC method, which combines Metropolis–Hastings algorithm and Gibbs sampler, referred to as Metropolis–Hasting-within-Gibbs [17]. It is known that the most popular MCMC method is the Gibbs sampler which requires knowledge of the full conditional probability density functions (pdfs) of all the parameter of interest. In our case, however, since the analytic determination of the full conditional pdfs of all the parameters of interest is not possible, we have integrated Metropolis–Hasting algorithm within the Gibbs sampler to be able to draw samples from those parameters whose conditional pdfs cannot be expressed analytically.

For the time-varying channels, we model the transmitter-to-relay and the relay-to-receiver channels using stationary first-order Gaussian autoregressive (AR) processes whose second-order statistics are matched to that of the channel fading processes. Such modeling enables us to develop particle filtering based algorithms which are implemented by choosing a convenient hybrid importance function [18] which is a product of a posterior and a prior pdf.

For both channel models, time-varying and quasi-static, we considered two different approaches in the development of their respective algorithms. In the first approach, we used a signal model that contains parameters that explicitly represent the transmitter-to-relay and relay-to-receiver channels. The first algorithms, therefore, keep track of the estimates of both channels while detecting the transmitted data. In the second approach, on the other hand, we transform the signal model of the RCS into an equivalent signal model of a point-to-point communication system that contains only one effective channel and a non-Gaussian noise. For this compact representation, we provide the probabilistic model of the effective channel and an approximate model for the additive noise. Since the effective channel is a product of the transmitter-to-relay and the relay-to-receiver channels, both assumed circularly-symmetric complex Gaussian pdfs, we show that the marginal pdfs of the real and imaginary components of the effective channel are Laplace pdfs. We, therefore, model the effective quasi-static channel by a complex Laplace pdf. Similarly, we represent the effective time-varying channel model, which is a product of two complex Gaussian first-order AR processes, by a single complex Laplace AR process [19].

1.1. Contribution and related work

As mentioned earlier, simulation-based Bayesian methods, specifically MCMC and particle filtering techniques, have been extensively applied to channel estimation and data detection problems. A good review on the application of particle filtering for single link communication problems can be found in [3]. A common approach in such problems is to represent the transmission process of the communication system in a state-space form by modeling the time-varying channel using a single complex Gaussian AR process. Such formulation allows the application of particle filtering techniques by selecting a posterior or prior importance function. To design more efficient algorithms, most proposed work used mixture Kalman filter [20], also refereed as Rao-Blakwellized filter, that combines Kalman filtering for channel estimation and particle filtering for data detection [6,7].

Furthermore, notable early work in [1,21,2] has tackled the problem of equalization and data detection in quasi-static multipath channels using MCMC methods. Also, over the years, several other works that deal with a single and multiple carrier modulation scheme in SISO and MIMO systems have applied MCMC methods [22]. The application of MCMC methods for communication problems essentially followed the same approach, and resulted in developing Gibbs sampler based algorithms. Such an approach results in a mathematical tractable structure, which means the conditional pdfs of all the parameters are expressed in analytic form, primarily because the problem formulation assumes Rayleigh faded channels, modeled by complex Gaussian coefficients.

In this paper, we deal with data detection in a relay-based communications which has its own unique challenges. The specific contributions of the paper are summarized as follows:

1. The paper extends further the application of these simulation-based Bayesian methods to RCSs. Such extension presents a different challenge because of the uniqueness of the statistical characteristics of relay-channels arising from the presence of cascades of channels. When applying MCMC methods for data detection in an RCS, unlike in a single channel communication system, an algorithm that is based solely on the Gibbs sampler cannot be obtained because the full conditional pdfs of all the parameters of interest cannot be derived in closed forms. We have, therefore, circumvented the problem by developing algorithms that combine the Gibbs sampler and Metropolis–Hasting algorithm.
2. By deriving the probabilistic characteristics of the overall relay-channel, we have developed a single channel model that represents the cascade of channels of a single-hop quasi-static relay-channel. We also extended such modeling to the time-varying relay-channel, and we represented its fading process as a Laplace AR model. Such a compact representation of the channel allows us to reduce the number of nuisance parameters to be tracked in the data detection problem.
3. The efficiency of particle filtering algorithms depends on the choice of the proposal density or importance function. The selection of a good importance function is, therefore, a critical step in the development of particle filtering algorithms. For our problem, where there is a cascade of channels, we have selected a hybrid important density [18] that is a product of the posterior density of one of the channels and a prior density of the data symbols. Such a choice of an important density allows us to develop a mixture Kalman filter based algorithm, a more efficient variant, for joint channel estimation and data detection in RCSs.

The paper is organized as follows. We present the signal model in Section 2. Section 3 describes the different channel models considered. We present MCMC and particle-filtering-based algorithms in Section 4 and Section 5 respectively. Complexity of the algorithms is discussed in Section 6, simulation results are provided in Section 7 and, finally, conclusions are given in Section 8.