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Parameter estimation and channel reconstruction based on compressive sensing for ultra-wideband MB-OFDM systems

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ABSTRACT

Multi-band orthogonal frequency-division multiplexing (MB-OFDM) is an important transmission technique for ultra-wideband (UWB) communication. One of the challenges for practical realization of these UWB MB-OFDM systems is the estimation of the channel. In UWB MB-OFDM, the channel can be modelled as sparse, and channel estimation (CE) based on compressed sensing (CS) can be used. However, the existing techniques all require prior knowledge of some channel parameters, which are not known in practice, e.g. the dictionary size, corresponding to the effective duration of the channel impulse response (CIR), and the sparsity of the CIR. Therefore, in this paper, we propose a CS-based channel parameter estimation method to estimate the dictionary size and the sparsity based on a pilot preamble of which the duration is shorter than the total duration of the CIR. Using the resulting parameter estimates, we reconstruct the CIR with the compressive sampling matching pursuit (CoSaMP) method. We show that the proposed algorithm is able to accurately estimate the sparsity and the dictionary size, and can effectively reconstruct the CIR for channels that are either based on a mathematical model or real, measured channels. Moreover, as the algorithm has acceptable complexity, the proposed method is suitable for practical use.

1. Introduction

Multi-band orthogonal frequency-division multiplexing (MB-OFDM) is a technique that is considered as one of the most promising techniques for ultra wideband (UWB) transmission, thanks to its ability to mitigate the effects of multipath fading and interference, and to achieve a high spectral efficiency at a relatively low cost [1,2]. One of the issues that needs to be solved in practical UWB MB-OFDM systems comprises the estimation of the channel. To meet this challenge, UWB MB-OFDM adopts a frame-based transmission [3], where pilot sequences are included in the frame preamble for channel estimation (CE). However, as the channel impulse response (CIR) in UWB MB-OFDM is very long, long pilot preambles must be used to accurately estimate the channel. As long pilot preambles limit the data throughput, often the pilot preamble is shortened. Because of this shorter preamble, traditional channel estimators, such as least-squares (LS), maximum-likelihood (ML) and minimum mean-squared error (MMSE) estimators [4–7], fail to accurately estimate the CIR.

In indoor environments, typically the propagation environment is complex, and results in many reflections. At the same time, the resolution of the ultrawideband signal is very high, implying the system can identify many of the multipath components. As a consequence, the channel impulse response will typically be very long. However, measurements of the UWB indoor channel show that the multipath components are strongly clustered, implying the channel impulse response, although being widely dispersed in time, only contains a limited number of non-zero contributions, i.e. the channel can be modelled as sparse. For example, [8,9] demonstrate that indoor channel models considered for the IEEE 802.15.4a standard [10] are sparse. Moreover, this sparsity is shown to be enlarged when the signal resolution increases [9]. Also the different channel models for the IEEE 802.15.3a standard [11] can be described with a limited number of non-zero channel taps. Besides the theoretical channel models considered in the literature, we also performed a measurement campaign in a laboratory environment, and show in this paper that the resulting channel is sparse. Consequently, we can use compressive sensing (CS) methods [12,13] to reconstruct the CIR and achieve channel estimation. Recently, several CE

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algorithms based on CS for UWB communication have been developed [8,14–16]. In [8], the applicability of CS for UWB channel estimation is investigated, and the authors employ standard Matching Pursuit (MP) algorithms for CS, such as subspace pursuit (SP) [17], orthogonal matching pursuit (OMP) [18] and compressive sampling matching pursuit (CoSaMP) [19], to accurately reconstruct the CIR. In [14], the authors propose four practical dictionaries to increase the sparsity of UWB signals, so that the UWB signals can be reconstructed more efficiently. In [15], another CS technique, i.e. the Bayesian CS (BCS) algorithm [20], is employed to reconstruct UWB signals and obtain CE. Although the BCS algorithm achieves a better performance than the MP algorithms, it requires intensive computations, raising a barrier for practical implementation. In [16], a CS dictionary, called eigen-dictionary, is proposed, exploiting the statistical sparsity of UWB signals where the channel structure exhibits several clusters of significant channel coefficients. Based on this structure, two novel BCS algorithms are proposed to efficiently reconstruct UWB CIR. Common to all these CS-based CE algorithms is that they require prior knowledge of the parameters of the underlying CIR model, which is not available in practice. Without the knowledge of these parameters, the CIR can not be estimated accurately, deteriorating the performance of UWB MB-OFDM systems.

In this paper, we extend the CoSaMP algorithm from [19], which combines low complexity and good CE performance, to autonomously estimate the required channel parameters. The CoSaMP algorithm requires the knowledge about the dictionary size, of which the optimal value is strongly correlated to the effective CIR duration, i.e. the duration of the part of the CIR containing the dominant channel components, and the sparsity of the channel, i.e. the number of non-zero channel taps. Optimally, the dictionary size and sparsity must be estimated jointly. Several classical algorithms exist to achieve this joint estimation, e.g. the simplex algorithm [21]. However, the computational burden of these algorithms is very high, and therefore limit the applicability of these joint estimators. Therefore, as main novelty, we propose in this paper an algorithm that has low complexity compared to the above-mentioned joint estimation algorithm. To this end, we first show that, although the dictionary size and sparsity are correlated, the optimal value of the dictionary size becomes essentially independent of the sparsity if the sparsity is sufficiently large. Based on this observation, we propose a two-step approach, where in the first phase, the optimal dictionary size is estimated, while in the second phase, the optimal value of the sparsity is obtained. In both phases, the algorithm adaptively searches for the optimal value of the parameter, using the pilot sequence included in the preamble. We show that the proposed adaptive CS-based parameter estimation algorithm not only can be applied to channels simulated based on a mathematical model, but also is able to exactly reconstruct the CIR measured in realistic scenarios. Although the proposed algorithm is sub-optimal in the sense that the mean-squared error of the resulting channel estimation is slightly higher than for the case where the simplex method is used, the resulting complexity is much smaller than with the simplex method, e.g. for short pilot preambles, the complexity of the proposed algorithm is 10 times lower than with the simplex method, and the difference in complexity increases when the length of the preamble increases. Further, we compare the performance of the proposed algorithm with state-of-the-art algorithms, and demonstrate that the proposed algorithm performs well, even if the pilot preamble is considerably shortened.

The rest of the paper is organized as follows. In Section 2, we introduce the channel model used for MB-OFDM systems and describe the measurement setup used to obtain the sparse measured channel. In Section 3, we briefly explain how CS is applied to the estimation of sparse channels, and we discuss the influence of the dictionary size and sparsity on channel reconstruction. The algorithm to estimate the dictionary size and the sparsity is introduced in Section 4. Further, we evaluate the complexity of the proposed algorithm in this section. In Section 5, we evaluate the performance of the proposed algorithm and compare its performance with that of state-of-the-art algorithms. Finally, the conclusions are given in Section 6.

2. Sparse channel

In this section, first we briefly introduce the CM for the IEEE 802.15.3a standard [11], suitable for UWB MB-OFDM systems that was used to generate the simulated channels, and then we describe the measurement setup that was used to obtain sparse measured channels to test our algorithm in realistic scenarios.

2.1. Channel model

The channel impulse response considered for the IEEE 802.15.3a standard [11] consists of a tapped-delay line model containing L clusters of K multipath components:

$$h(t) = X\sum_{l=1}^{L}\sum_{k=1}^{K}\alpha_{k,l}\delta(t-T_l-\tau_{k,l}), \tag{1}$$

where $\alpha_{k,l}$ are the multipath gain coefficients, T_l is the delay of the lth cluster, $\tau_{k,l}$ is the delay of the kth multipath component relative to the lth cluster arrival time T_l and the prefactor X corresponds to the log-normal shadowing. The delays T_l and $\tau_{k,l}$ follow an exponential distribution with cluster arrival rate Λ and ray arrival rate λ, respectively:

$$P(T_l|T_{l-1}) = \Lambda\exp[-\Lambda(T_l-T_{l-1})] \tag{2}$$

$$P(\tau_{k,l}|\tau_{k-1,l}) = \lambda\exp[-\lambda(\tau_{k,l}-\tau_{k-1,l})]. \tag{3}$$

We select $\tau_{0,l}=0$. The multipath gain coefficient $\alpha_{k,l}$ in (1) can be decomposed as follows:

$$\alpha_{k,l} = p_{k,l}\zeta_l\beta_{k,l}, \tag{4}$$

where $p_{k,l}$ equiprobably takes the values ± 1 to account for signal inversions due to reflections, ζ_l represents the fading associated with the lth cluster, and $\beta_{k,l}$ corresponds to the fading associated with the kth ray of the lth cluster. This fading coefficient $\zeta_l\beta_{k,l}$ follows a log-normal distribution:

$$20\log_{10}(\zeta_l\beta_{k,l}) \sim N(\mu_{k,l}, \sigma_1^2+\sigma_2^2), \tag{5}$$

where σ_1 is the standard deviation from the cluster log-normal fading term ζ_l and σ_2 is the standard deviation from the ray log-normal fading term $\beta_{k,l}$. Further, defining the cluster decay factor Γ and ray decay factor γ, the mean $\mu_{k,l}$ can be written as:

$$\mu_{k,l} = \frac{10\ln(\Omega_0 - 10T_l/\Gamma - 10\tau_{k,l}/\gamma)}{\ln(10)} - \frac{(\sigma_1^2+\sigma_2^2)\ln(10)}{20}, \tag{6}$$

where Ω_0 is the average energy of the first path of the first cluster. Finally, the log-normal shadowing factor X of the total multipath power from (1) has the distribution:

$$20\log_{10}(X) \sim N(0, \sigma_x^2), \tag{7}$$

where σ_x is the standard deviation of the log-normal shadowing of the total multipath power.

The parameters of the four channel models presented in [11] are listed in Table 1. These four models consider communication among UWB devices located within a range of less than 10 m. Specifically, CM1 and CM2 model the line-of-sight (LOS) and non-LOS (NLOS) channel environments, for ranges smaller than 4 m. For larger ranges, the NLOS models CM3 and CM4 are used, with emphasis on the strong delay dispersion Γ from CM4 [2]. In this paper, we consider discrete-time channel models derived from the