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ENERGY EFFICIENT COMMUNICATION NETWORKS FOR WIRELESS AND MOBILE COMMUNICATION

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Abstract: The data traffic in wireless networks is steadily growing. The long-term trend follows Cooper's law, where the traffic is doubled every two-and-a-half year, and it will likely continue for decades to come. The data transmission is tightly connected with the energy consumption in the power amplifiers, transceiver hardware, and baseband processing. The relation is captured by the energy efficiency metric, measured in bit/Joule, which describes how much energy is consumed per correctly received information bit. While the data rate is fundamentally limited by the channel capacity, there is currently no clear understanding of how energy-efficient a communication system can become. Current research papers typically present values on the order of 10 Mbit/Joule, while previous network generations seem to operate at energy efficiencies on the order of 10 kbit/Joule. Is this roughly as energy-efficient future systems (5G and beyond) can become, or are we still far from the physical limits? These questions are answered in this paper. We analyze a different cases representing potential future deployment and hardware characteristics.

1. INTRODUCTION

WITH the increasing demand for higher spectral efficiency and reliability in the next generation wireless communications, multiple-input multiple-output (MIMO) systems have been receiving great attention for their ability in improving the transmission rate and error performance [1]–[3]. Recently, a novel MIMO scheme called spatial modulation (SM) has emerged as an appealing candidate to fulfill the spectral and energy efficiency requirements of the next generation wireless communication systems [4]–[10]. In SM, information bits are conveyed by not only the modulated symbol but also the index of the active

transmit antenna. Compared with classical MIMO, SM has a number of advantages, including reduced interchannel interference, relaxed inter-antenna synchronization requirements, and reduced receiver complexity [6], [7]. Owing to its various advantages, design and analysis of SM transmission in various scenarios, e.g., adaptive SM [11]–[13], generalized SM [14]–[16], and energy evaluation of SM [17]–[20], are extensively investigated. Specially, for practical multipath fading channels, single-carrier aided SM [21]–[23] is conceived as an appealing technique to eliminate inter-antenna interference and

achieve high energy efficiency with only one active antenna at any time instant. Compared with single-carrier transmission, orthogonal frequency division multiplexing (OFDM) is usually more favored for multipath fading channels as it facilitates low-complexity receiver design by converting the multipath fading channel into several parallel flat fading channels in the expense of an increased peak-to-average-power ratio (PAPR) at the transmitter.

For the past centuries, people desire to communicate with each other in a convenience and economical way. Due to this demand, communications has been a vibrant field of research for more than hundred years. Thanks to the development of Very Large Scale Integration (VLSI) and Signal Processing technology since the 1960s, wireless communications has become one of the most significant research areas in the field of modern communications, [1]. A tremendous advantage of wireless communication compared with wired communication is that it does not require any physical cables. This superiority not only enables devices to work anywhere without considering the limitation of the wires but also saves the money.

2. LITERATURE SURVEY

In the optimal number of active subcarriers selection problem is investigated. In recent times, the performance of OFDM-IM is analyzed in terms of ergodic achievable rate [38] and average mutual information [39]. Due to the advantages of OFDM and MIMO transmission techniques, the combination of them has been regarded as a promising solution for enhancing the data rates of next

generation wireless communications systems. More recently, by combining OFDM-IM with MIMO transmission techniques, a novel MIMO-OFDM with index modulation (MIMO-OFDM-IM) scheme is presented in [40], which exhibits the potential to surpass the classical MIMO-OFDM. Specifically, by deactivating a subset of subcarriers, MIMO-OFDM-IM has the potential to achieve much better BER performance than classical MIMO-OFDM, resulting in higher energy efficiency for practical systems. Then, the error performance of the MIMO-OFDM-IM scheme is investigated theoretically for different types of detectors in [41] and its adaptation to visible light communications systems is presented in [42]. In this scheme, since each transmit antenna transmits an independent OFDM-IM block, its spectral efficiency can reach N_t times that of OFDM-IM, where N_t denotes the number of transmit antennas. Inheriting from OFDM-IM, MIMO-OFDM-IM is also able to provide an interesting trade-off between the spectral efficiency and the error performance by adjusting the number of active subcarriers in each OFDM-IM subblock. However, due to the dependence of the subcarrier symbols within each OFDM-IM subblock and the strong inter-channel interference (ICI) between the transmit antennas of the MIMO-OFDM-IM system, it becomes much more challenging to detect the active subcarrier indices and modulated symbols. Although the ML detector is able to achieve optimal performance, it necessitates an exhaustive search with prohibitive computational

complexity, which makes itself impractical for MIMO-OFDM-IM. To reduce the detection complexity, several low complexity detectors, e.g., simple minimum mean square error (MMSE) detector, log-likelihood ratio (LLR) based MMSE detector, and ordered successive interference cancellation (OSIC) based MMSE detector are proposed for the detection of MIMO-OFDM-IM [40], [41]. However, those existing low complexity detectors suffer from a significant error performance loss compared to the ML detector. Therefore, the design of low-complexity detection algorithms for MIMO-OFDM-IM with near-optimal error performance remains an open as well as challenging research problem.

In this paper, in order to achieve near-optimal error performance while maintaining low computational complexity, two types of detection algorithms based on the sequential Monte Carlo (SMC) theory are proposed for MIMO-OFDM-IM. By regarding each OFDM-IM subblock as a super modulated symbol drawn from a large finite set, the first type of detector draws samples independently at the subblock level. Although it is capable of achieving near-optimal performance with substantially reduced complexity, its decoding complexity can be still unsatisfactory when the size of the OFDM-IM subblock grows much larger. To further reduce the complexity, the second type of detector is proposed to draw samples subcarrierwise from the modified constellation with a much smaller size. To meet the constraint on the legal active subcarrier combinations within

each OFDM-IM subblock, the second type of detector is coupled with a carefully designed examination method to avoid illegal samples. Thanks to the effectiveness of the deterministic SMC sampling and legality examination, it only suffers from a marginal error performance loss. Finally, computer simulation and numerical results in terms of BER and number of complex multiplications (NCM) corroborate the superiority of both proposed detection methods.

3. SMC AND SEQUENTIAL STRUCTURE FOR MIMO-OFDM

The SMC method, also referred to as particle filter, is a class of the sampling based sequential Bayesian inference methodologies for general dynamic systems, which has been widely applied in wireless communications [43]–[48]. In the following, we will first briefly introduce the concept of the deterministic SMC and then construct the sequential structure for MIMO-OFDM. In most applications of digital communications, the transmitted signals take values from a finite set and the received signals are the superimposition of transmitted signals corrupted by Gaussian noise. The a posteriori distribution can be thus computed by performing an exhaustive search over all possible realizations of the transmitted signal block, whose computational complexity grows exponentially with the size of the transmitted signal block. Instead of the exhaustive search and computation, the objective of the deterministic SMC method is to numerically approximate the a posteriori distributions of

the states of some Markov processes, given some noisy and partial observations. At each sampling interval, we draw symbol samples from the given finite set to construct new sequential particles, and then update their corresponding importance weights, where an illustrative example is shown in Fig. 3. Specifically, after calculating the importance weights for all hypotheses generated by the previous particles $n(X_{t-1})$ ($b \in \beta$), we only retain β most promising hypotheses associated with the highest importance weights as the new particles $n(X_t)$ ($b \in \beta$) while discarding other hypotheses immediately at each sampling interval. More detailed descriptions of the deterministic SMC concept will be given in Section IV with the proposed algorithms.

It has been shown that the deterministic SMC-based detectors can achieve near-ML performance with much lower computational cost to the receiver for various communications systems [43]–[48]. Moreover, attributed to its nature of being soft-input and soft-output, SMC based detection can also be efficiently employed in coded communication systems. However, to apply the deterministic SMC theory in a specific system, it is essential to construct the sequential structure based on the observed signals for the sampling procedure, which varies for different communication scenarios.

4. LOW-COMPLEXITY DETECTORS FOR MIMO-OFDM-IM

In this section, we will develop two types of SMC-based detectors by using the structure of (10) as the kernel for MIMO-OFDM-IM.

As will be shown by computer simulations, the new algorithms can avoid error propagation successfully and provide near-optimal error performance for MIMO-OFDM-IM.

After the lower triangular operation, the sequential structure in (10) can be exploited by applying the SMC method to draw samples starting from the first transmit antenna and ending to the last one. Indeed, if we simply regard each OFDM-IM subblock $x_{g,t}$ as a super modulated symbol drawn from a large finite set, we have the a posteriori distribution of $\{x_{g,t}\}_{t=1}^{N_t}$ conditioned on $\{z_{g,t}\}_{t=1}^{N_t}$ as where $z_{g,t} = [z_{g,t}(1) z_{g,t}(2) \cdots z_{g,t}(N)]^T$ denotes the observed subblock in the t -th ($1 \leq t \leq N_t$) branch of the receiver after the lower triangular operation in (10), and $X_{g,t} = \{x_{g,t} \}_{t=0}^1$. Based on (11), we construct the sequence of probability distributions $n P_{X_{g,t} | Z_{g,t}} \}_{t=1}^{N_t}$, which can be expressed as where $Z_{g,t} = \{z_{g,t} \}_{t=0}^1$. From the perspective of the probability theory, our aim is to estimate the a posteriori probability of each OFDM-IM subblock. based on the observed subblocks $\{z_{g,t}\}_{t=1}^{N_t}$, where $\Phi^* = \{\Phi_i\}_{i=1}^{N_{CMK}}$ with $|\Phi^*| = N_{CMK}$ denotes the set including all possible realizations of the OFDM-IM subblock. Instead of the direct computation of (13), which is too computationally expensive, we seek to numerically approximate (13) by using the deterministic SMC theory to substantially reduce the complexity at the receiver. Let $(X_{g,t})$ ($b \in \beta$) be the particles drawn by the SMC method at the t -th sampling interval on the basis of subblock, where β denotes the total number

of particles. To implement the SMC method, we first generate a set of incomplete particles for the OFDM-IM subblocks, and then update the corresponding importance weights for those particles with respect to the distribution of (11) until the subblock at the last antenna is reached. Moreover, to update the importance weights, it is crucial to design the trial distribution which minimizes the variance of the importance weights conditioned upon the previous particles and the observed signals [50]. Under the criterion of minimum conditional variance of the importance weights, we simply choose the trial distribution as for $t = 1, \dots, N_t$. Proposition 1: With the trial distribution given in (14), the importance weight for the SMC can be updated according to (5) where $p(z|g, t) = X(g, t-1)$ can be regarded as the prediction distribution of the current observed subblock $z(g, t)$ under the condition of the previous particle $X(g, t-1)$.

5. PROPOSED METHOD

A new wireless technology generation is introduced every decade and the standardization is guided by the International Telecommunication Union (ITU), which provides the minimum performance requirements. For example, 4G was designed to satisfy the IMT-Advanced requirements [1] on spectral efficiency, bandwidth, latency, and mobility. Similarly, the new 5G standard [2] is supposed to satisfy the minimum requirements of being an IMT-2020 radio interface [3]. In addition to more stringent requirements in the aforementioned four categories, a new metric has been included in [3]: energy

efficiency (EE). A basic definition of the EE is [4], [5] $EE [\text{bit/Joule}] = \text{Data rate} [\text{bit/s}] / \text{Energy consumption} [\text{Joule/s}]$. (1) This is a benefit-cost ratio and the energy consumption term includes transmit power and dissipation in the transceiver hardware and baseband processing [5], [6]. A general concern is that higher data rates can only be achieved by consuming more energy; if the EE is constant, then 100× higher data rate in 5G is associated with a 100× higher energy consumption. This is an environmental concern since wireless networks are generally not powered from renewable green sources. It is desirable to vastly increase the EE in 5G, but IMT-2020 provides no measurable targets for it, but claims that higher spectral efficiency will be sufficient. There are two main ways to improve the spectral efficiency: smaller cells [6], [7] This paper was supported by ELLIIT and grants from the Swedish Foundation for Strategic Research (SSF) and the Swedish Research Council (VR). and massive multiple-input multiple-output (MIMO) [8], [9]. The former gives substantially higher signal-to-noise ratios (SNRs) by reducing the propagation distances and the latter allows for spatial multiplexing of many users and/or higher SNRs. Since these gains are achieved by deploying more transceiver hardware per km², higher spectral efficiency will not necessarily improve the EE; the EE first grows with smaller cell sizes and more antennas, but there is an inflection point where it starts decaying instead [10]. The bandwidth is fixed in these prior works, but many other parameters are optimized for maximum EE. There are other

non-trivial tradeoffs, such as the fact that transceiver hardware becomes more efficient with time [6], [11], so the energy consumption of a given network topology gradually reduces. While the Shannon capacity [12] manifests the maximal spectral efficiency over a channel and the speed of light limits the latency, the corresponding upper limit on the EE is unknown. A comprehensive study of the EE of 4G base stations is found in [13]. It shows that a macro site delivering 28 Mbit/s has an energy consumption of 1.35 kW, leading to an EE of 20 kbit/Joule. Recent papers report EE numbers in the order of 10 Mbit/Joule [5], [14], [15] when considering future 5G deployment scenarios and using estimates of current transceivers' energy consumption. There is also numerous papers that consider normalized setups (e.g., 1 Hz of bandwidth) that give no insights into the EE that can be achieved in practice. Finally, the channel capacity per unit cost was studied for additive white Gaussian noise (AWGN) channels in [16], which is a rigorous but normalized form of EE analysis. The goal of this paper is to analyze the physical EE limits in a few different cases and, particularly, give practically relevant numbers on the maximum achievable EE.

6. CONCLUSION

The answer to the question "How energy-efficient can a wireless communication system become?" depends strongly on which parameter values can be selected in practice and the energy consumption modeling. If it is modeled to capture the most essential hardware characteristics, the optimal EE is achieved for a particular ratio

of the transmit power P and bandwidth B , which typically corresponds to a low SNR. Any data rate can be achieved by jointly increasing P and B while keeping the optimal ratio. The physical upper limit on the EE is around 1 Pbit/Joule. For practical number of antennas and channel gains, we can rather hope to reach EEs in the order of a few Tbit/Joule (as in Fig. 4) in future systems

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