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ANALYASIS OF MIMO-OFDM SYSTEM IN CARRIER FREQUENCY OFFSET USING PARTICLE FILTER

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ABSTRACT: A particle filter is proposed to perform joint estimiation of the carrier frequency offset (CFO) and the channel in multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) wireless communication systems. It marginalizes out the channel parameters from the sampling space in sequential importance sampling (SIS), and propagates them with the Kalman filter. Then the importance weights of the CFO particles are evaluated according to the imaginary part of the error between measurement and estimation. The varieties of particles are maintained by sequential importance resampling (SIR). Simulation results demonstrate this algorithm can estimate the CFO and the channel parameters with high accuracy. At the same time, some robustness is kept when the channel model has small variations

KEYWORDS: Carrier Frequency Offset,Multiple-Input Multiple-Output (MIMO), Orthogonal Frequency Division Multiplexing (OFDM), sequential Monte Carlo, Particle Filter.

1.INTRODUCTION

The combination of orthogonal frequency division multiplexing (OFDM) and multiple antennas at both the transmitter and the receiver, referred to as multiple input multiple-output (MIMO). In the MIMO-OFDM transmission system the carrier frequency offset (CFO) induced by the local oscillator and the Doppler shift results in the interference of sub-carriers and further incurs an error floor effect. It is required to estimate and compensate for the CFO at the receiver side. Moreover, the unknown channel parameters mixed in the transmission will deteriorate the acquisition condition in practice .In contrast to frequency synchronization schemes of single-input single-output (SISO)-OFDM systems this problem is extended to multi-dimensional parameter acquisition in MIMO systems. Hence, it incurs much difficulty for the coherent detection. Various methods have been investigated to estimate multiple time-invariant frequency offset and channel parameters, such as maximum-likelihood estimation correlation-based method, expectation maximization (EM) and iterative methods. They all use the Cramer Rao bound as the precision reference. In addition, an extended Kalman filter (EKF) is designed to track time-variant parameters.

Recently, a sequential Monte Carlo approach in the Bayesian framework has been widely investigated in the wireless communication systems. These particle filtering algorithms estimate the state information with a posterior probability. Moreover, they can achieve theoretical optima in the presence of nonlinear and non-Gaussian models. In comparison with other nonlinear estimation methods such as EKF and unscented Kalman filter (UKF), a particle filter will yield more accurate results along with the flexibility of the algorithm design .However, in terms of this high-dimensional parameter estimation, it is very hard to get appropriate particles with small distribution variance on each dimension by the general sequential importance sampling (SIS) method.

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When the transmit/receive antennas in a MIMO system share one oscillator, the difference of CFOs among different antenna pairs can be negligible. Under such a scenario, the particle filter is investigated to marginalize out the unknown time-variant Rayleigh channel from the sampling space. The channel is estimated by the Kalman filter on the assumption that its response model is known. The particle weights of CFO are evaluated according to the estimation error. Simulation results demonstrate the algorithm can estimate the CFO and the channel jointly with high accuracy, as well as its robustness to small variations of the channel model.

I. SYSTEM MODEL

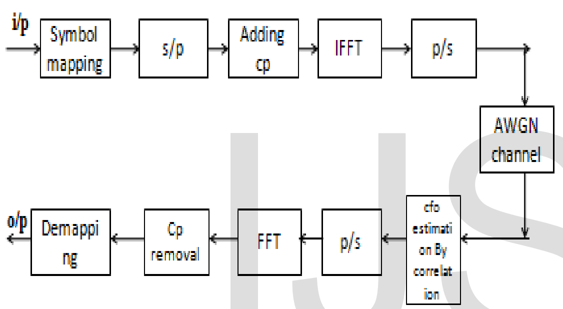

Figure1 Block diagram for OFDM SIGNAL GENERATION

2.1 MIMO OFDM System:

Consider an uplink OFDM system with N subcarriers and K active users. The base station (BS) and each active user are equipped with Mr and Mt antennas, respectively. Each user is assigned Nk exclusive subcarriers, we denote the index set of carriers assigned to the k-th user as where $1 \leq il \leq N$ for l = 1, 2, Nk. The proposed algorithms are applicable to any carrier assignment scheme (CAS). Note that even though we are using orthogonal subcarriers, self-interference and MAI are inevitable due to CFOs Denote by the data symbols transmitted by the k-th user from the p- th transmit antenna over the n-th OFDMA block. For convenience, we assume that the data symbols are taken from the same complex-valued finite alphabet and independently identically distributed. The i-th entry of is non-zero if and only if .next, is converted to the corresponding time-domain vector by an N-point inverse discrete Fourier transform (IDFT):

$$d_k^p(n) = w^H d_k^p(n) \qquad (1)$$

Where is the IDFT matrix. To prevent inter-symbol interference (ISI), a cyclic prefix (CP) of Ng symbols is appended in front of each IDFT output block. The resulting vector of length is digital-to-analog converted by a pulse-shaping filter with a finite support on [0, Td] where with 1/(NTs) being the subcarrier spacing. Finally, the analog signal from the pulse-shaping filter is transmitted from the p-th antenna over the channel.

That is, be the normalized carrier frequency offset with respect to (w.r.t.) the carrier spacing 1/(NTs) between transmit antennas of the k-th user and the q-th receive antenna of the BS. In the presence of CFOs, the received vector signal after removing the guard interval becomes

$$r^q(n) = \sum_{k=1}^{k} \Delta(\in_k^q(n) \sum_{p=1}^{mt} D_k^p(n) h_k^{p.k}(n) + v^{q(n)} 0$$

$$= \sum_{k=1}^{k} D_k^p(n) h_k^{p.k}(n) + v^{q(n)} \qquad (2)$$

Recall that the CP length equals the channel length plus timing offset. Under such an , the timing errors do not explicitly appear in the received signal model. Thus, we have suppressed the timing errors in (2). Several approaches have been proposed to model the time-varying channels and frequency offsets in mobile environments. Since we assume a normalized Doppler spread $fDTd \ll 1$,we adopt the following first-order autoregressive (AR) parametric model widely used to characterize the time-varying frequency offset and channel responses.

$$\in_k^q(n) = \alpha_{k\,E}^q \in_k^q(n-1) + w_{k\,E}^q(n)$$

$$h_k^q(n) = \alpha_{k\,E}^q h_k^q(n-1) + w_{k\,h}^q(n) \qquad (3)$$

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Furthermore, we assume that Note that we assume independent fading across transmit antennas and multi-paths. The time variation in CFO in (4) arises from (a) local oscillator instability due to temperature/voltage variations and (b) changes in relative platform Doppler velocity. In the next section, we propose a pilot-aided parallel Schmidt extended particle filter approach to estimate based on the received signal (n), assuming exact knowledge of and in the BS.

The incoming input binary streams are first mapped into constellation points according to any of the digital modulation schemes such as QPSK/QAM. In QPSK (Quadrature Phase Shift Keying) modulation, the incoming binary bits are combined in the form of two bits and are mapped into constellation point. The N constellation points are modulated using N sub- carriers whose carrier frequencies are orthogonal in nature. The modulation is similar to taking inverse discrete/fast fourier transform (IDFT/IFFT) operation. The output of N point (IFFT) block is the OFDM signal. Now the N OFDM signal samples are combined and then transmitted i.e., the parallel samples are now converted into serial sequence and then it is transmitted. The OFDM baseband signal at the transmitter is expressed as in

$$x(n) = 1/\sqrt{n}\sum_{k=0}^{N-1} x(k)e^{j2\pi nk/n}. \quad 0<n<N-1 \qquad (4)$$

where

n -time domain sample index
X (k) -modulated QPSK data symbol on the kth subcarrier
N -total number of subcarriers and
x (n) -OFDM signal.

In order to maintain a signal to noise ratio (SNR) of 20 decibels or greater for the OFDM carriers, offset is limited to 4% or less than the inter carrier spacing which is simulated in the lower bound for the SNR at the output of the DFT for the OFDM carriers in a channel with AWGN and frequency offset is derived as and is given by

$$SNR \geq \left\{\frac{E_c}{N_0}\right\}\left\{\frac{sin\pi v}{\pi v^2}\right\}/\{10.594(\frac{E_c}{N_0})\}(\{sin\pi v)^2\} \qquad (5)$$

Ec is the energy of subcarrier, All the preamble based frequency offset estimation methods given in literature aims at accuracy and increasing the range of frequency offset estimation. The importance of frequency offset estimation in various high speed broadband wireless applications can be understood

2.2 CFO Estimation :

Particle filtering is a sequential sampling method built on the Bayesian paradigm. From the Bayesian theory, at sample k , the posterior distribution p(x0:k | r0:k) is the main entity of interest. However, due to the nonlinearity of the measurement equation, its analytical expression is not tractable. Alternatively, particle filtering can be applied to approximate this PDF by stochastic samples generated using a sequential importance sampling strategy. Particle filtering is an extension of the sequential methodology. It consists in recursively estimating the required posterior density function p(x0:k | r0:k) by a set of M random samples with associated weights, denoted by

$$\hat{p}\left(\frac{x_0}{\gamma_{0:k}}\right) = \sum_{J=1}^{M} \delta\left(x_{0:k} - x_{0:k}^{j}\right) w_k^{(j)} \qquad (6)$$

Where is drawn from the importance function is the Dirac delta function and is the normalized importance weight associated with the j-th particle. The weights are updated according to the

$$w_k^{(m)} \alpha \frac{p\left(\gamma_{\underline{k}} x_{0:k-1}^{(m)}, \gamma_{0:k}\right) p\left(\gamma_k x_{0:k-1}^{(m)}, \gamma_{0:k}\right)}{\pi(x_k^{(m)}/x_{0:k-1}^{m}\ \gamma_{0:k})} w_{k-1}^{m} \qquad (7)$$

After a few iterations, particle filtering is known to suffer from degeneracy problems. So we integrate a resampling step to select particles for new generations in proportion to the importance weightsThis is due to the fact that the particle filter is then only used to estimate the nonlinear states, while the remaining conditional linear-Gaussian states are estimated using the closed-form particle filter. In our case, conditionally on the nonlinear state variables the DSS model contains a linear substructure on h, subject to Gaussian noise. Using the Bayes' theorem, the posterior density function of interest can be written as

$$p\left(\frac{x_{0:k}}{\gamma_{0:k}}\right) = p\left(\frac{h}{(\theta_{0:k},\varepsilon_{0:k},\gamma_{0:k})(\theta_{0:k},\varepsilon_{0:k},\gamma_{0:k})}\right) \quad (8)$$

Where is analytically tractable and can be obtained via a particle filter associated with each particle. Indeed, the j-th PDF is a multi dimensional gaussian probability density function. The mean and the covariance can be obtained using the particle filtering equations given by the time update equations

$$h^{(j)}_{\frac{k}{k}-1} = h^{(j)}_{\frac{k}{k}-1} \quad \sum j_{\frac{k}{k}-1} = \sum j_{\frac{k}{k}-1} \quad (9)$$

2.3 Particle Filter:

A particle filter is a nonparametric implementation of the Bayes filter and is frequently used to estimate the state of a dynamic system. The key idea is to represent a posterior by a set of hypotheses. Each hypothesis represents one potential state the system might be in. The state hypotheses are represented by a set S of N weighted random samples

$$S = \{< S^{[i]}, W^{[i]} > i = 1, \dots \dots N\} \quad (10)$$

where s[i] is the state vector of the i-th sample and w[i] the corresponding importance
weight. The weight is a non-zero value and the sum over all weights is 1. The sample
set represents the distribution

$$p(x) = \sum_{i=1}^{N} w_i \; \delta_{s\,(i)(x)} \quad (11)$$

:

We are faced with the problem of computing the expectation that x ∈ A, where A
is a region. In general, the expectation Ep[f(x)] of a function f is defined as

$$E_p[f(x)] = \int p(x).f(x)dx \quad (12)$$

Let B be a function which returns 1 if its argument is true and 0 otherwise. We can
express the expectation that x ∈ A by

$$E_p[B(x\epsilon A)] = \int p(x).B(x\epsilon A)dx$$

$$\int \frac{p(x)}{\pi(x)}.\pi(x).B(x\varepsilon A)dx \quad (13)$$

where _ is a distribution for which we require that

$$p(x) > 0, \pi(x) > 0$$

Thus, we can define a weight w(x) a

$$w(x) = \frac{p(x)}{\pi(x)} \quad (14)$$

This weight w is used to account for the differences between p and the _. This leads to

$$\mathrm{E_p[B(x\epsilon A)]} = \int \mathrm{p(x).w(x).B(x\epsilon A)dx}$$

$$= \mathrm{E_\pi[w(x)B(x\epsilon A)]} \quad (15)$$

Let us consider again the sample-based representations and suppose the sample are drawn from. By counting all the particles that fall into the region A, we can compute the integral of over A by the sum over samples

$$\left[\int \pi(x)dx \approx 1/n \sum_{i=1}^{n} B(s \in A)\right] \quad (16)$$

FIGURES AND TABLES

3.1 CFO Estimation on SNR:

The increment of SNR estimation accuracy of channel tends to be higher .It can also be observed that the number of the particles is another direction Factor of the estimation accuracy

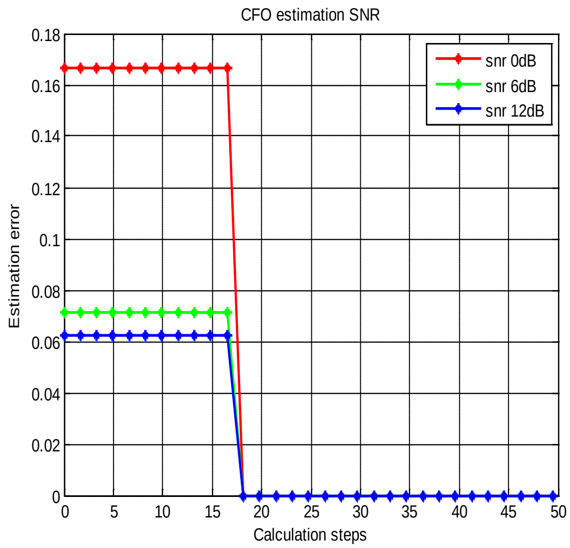

Figure2: CFO Estimation on SNR

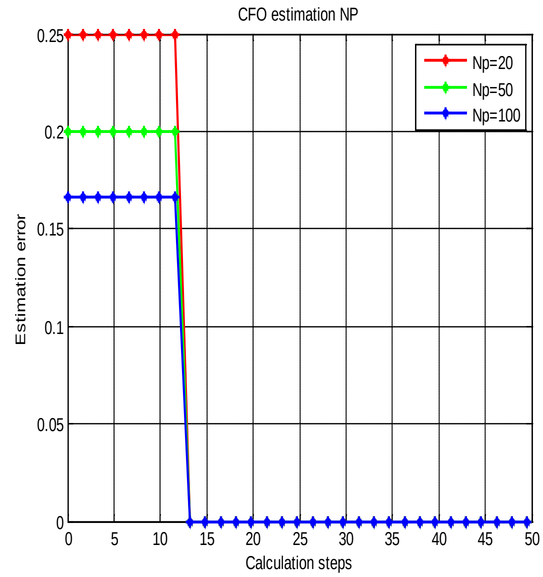

FIGURE 3: CFO Estimation on number of Particles

3.2 INFERENCE:

For SNR(db)	At Calculation steps	Estimation error
0	13.2	0.1667
6	13.2	0.07143
12	13.2	0.0625

Table1: Comparison for CFO Estimation SNR

3.3 CFO Estimation on number Of Particles:

As the of particles increase the estimation error will be lower. In addition the particle with large weights have large number than that of the particle with lower weight.

3.4 INFERENCE:

For NP	At Calculation steps	Estimation error
20	11.55	0.25
50	11.5	0.2
100	11.55	0.1667

Table2: Comparison for CFO Estimation NP

4.CONCLUSION

Particle filtering algorithm for frequency synchronization in MIMO-OFDM systems. It is based on the sequential Monte Carlo approaches in the Bayesian framework, and simplified to a one-dimensional particle sampling in order to improve the computation efficiency. Numerical simulation shows that the algorithm can obtain high accuracy of CFO and estimation performance. Additionally, it can simultaneously estimate time-varying CFO and channel. It also has some robustness to the variation of the channel model.

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