Partial Transmit Sequences for PAPR Reduction of OFDM Signals with Stochastic Optimization Techniques

Jung-Chieh Chen, *Member*, IEEE

Abstract —*This paper considers the use of the partial transmit sequence (PTS) technique in reducing the peak-to-average power ratio (PAPR) of an orthogonal frequency division multiplexing (OFDM) signal. The conventional PTS technique is highly successful in PAPR reduction for OFDM signals, but the considerable computational complexity for the required search through a high-dimensional vector space is a potential problem for practical implementation. To reduce the search complexity while still improving the PAPR statistics, stochastic optimization techniques such as the simulated annealing (SA) algorithm, Cross-Entropy (CE) method, and particle swarm optimization (PSO) have recently been proposed to search for a phase factor that reduces both the PAPR statistics and the computational load. In this paper, a novel stochastic optimization approach, that is, the electromagnetism-like (EM) algorithm, is applied to reduce the PAPR of an OFDM signal. The computer simulation results show that compared with the various stochastic search techniques developed previously, the proposed EM method obtains the most desirable PAPR reduction with low computational complexity.*[1]

Index Terms —Orthogonal frequency division multiplexing (OFDM), peak-to-average power ratio (PAPR), partial transmit sequence (PTS), electromagnetism-like (EM) algorithm, stochastic optimization technique

I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) has been widely used in a variety of digital transmissions including digital video/audio broadcasting, digital subscriber lines, and wireless local area networks [1][2] because of its ability to cope with the frequency selective fading of wideband communication with reasonable complexity. However, one major problem associated with OFDM is its high peak-to-average power ratio (PAPR) for the time-domain transmitted signal especially for a large number of subcarriers. As a result, when a high PAPR signal passes through a power amplifier (PA), the PA may be pushed to a saturation region, causing both in-band and out-of-band distortion.

To alleviate the PAPR of the OFDM system, many approaches [1]-[20] have been proposed including clipping, coding, and multiple signal representation techniques such as partial transmit sequence (PTS) and selected mapping (SLM). Among these methods, the PTS technique [3] is an efficient and a distortionless phase optimization technique for PAPR reduction by optimally combining signal subblocks. In a PTS scheme, the input data is divided into smaller disjoint subblocks. Each subblock is then multiplied by rotating phase factors, where the phase factor can be chosen freely within $[0, 2\pi)$. Subsequently, the subblocks are added to form the OFDM symbol for transmission. Accordingly, the objective of the PTS is to design an optimal phase factor for the subblock set that minimizes the PAPR.

PTS significantly improves PAPR performance, but unfortunately, finding the optimal phase factors is a complex, non-linear optimization problem. Moreover, the conventional PTS requires an exhaustive search from all combinations of allowed phase factors. It turns out that search complexity increases exponentially with the number of subblocks. To reduce search complexity, stochastic search techniques have recently been proposed [15]-[20] because they can obtain the desirable PAPR reduction with low computational complexity. Famous stochastic techniques for PAPR reduction include the simulated annealing (SA) algorithm [15][16], the Cross-Entropy (CE) method [17][18], and particle swarm optimization (PSO) [19][20].

Recently, Birbil and Fang proposed a novel population-based stochastic search method called electromagnetism-like mechanism (EM) for global optimization [21]. Inspired by the Coulomb's Law of electromagnetism, the EM method considers each particle (i.e., the solution) in the population to be an electrical charge and simulates the behavior of electrically charged particles. Through the attraction and repulsion of the charged particles, particles move towards optimality. Compared with genetic algorithms (GA), the EM requires neither coding nor encoding procedure as in the GA. Moreover, the method has the advantages of SA, that is, the particle's movement gradually slows down in the latter stages of iteration. In general, this method is similar to PSO, only it requires fewer particles. Most importantly, the EM method has shown its robustness in practice. It is also proven to exhibit global convergence with probability one [22].

Based on the above points, we state our interest to employ a novel PTS technique based on the EM algorithm to reduce the PAPR of OFDM signals through this paper. The simulations demonstrate that the proposed EM not only achieves significant PAPR reduction but also enjoys complexity advantages compared with the other well-known stochastic approaches.

[1]This work was supported in part by the National Science Council, Taiwan, under Grant NSC 98-2221-E-017-004.

J.-C. Chen is with the Department of Optoelectronics and Communication Engineering, National Kaohsiung Normal University, Kaohsiung 802, Taiwan. (e- mail: jc_chen@ieee.org)

Contributed Paper
Manuscript received 05/21/10
Current version published 09/23/10
Electronic version published 09/30/10.

This paper is organized as follows. In Section II, we describe the OFDM system model and PAPR problem definition. Next, the proposed EM algorithm is developed in Section III. Simulation results that compare the PAPR reduction performance of various stochastic optimization techniques including the proposed one are given in Section IV. The conclusions are presented in the last section.

II. SYSTEM MODEL AND PROBLEM DEFINITION

Consider an OFDM system with N subcarriers. The discrete-time transmitted OFDM signal is given by

$$x_t = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n e^{j2\pi nt/PN}, \; t = 1, 2, \cdots, PN-1, \quad (1)$$

where $j = \sqrt{-1}$, $\mathbf{X} = [X_0 \quad X_1 \quad \cdots \quad X_{N-1}]^T$ is an input symbol sequence, t stands for a discrete time index, and P is an integer that is larger or equal to 1 called over-sampling factor. When $P = 1$, the samples are achieved by using the Nyquist rate sampling. The PAPR of the transmitted signal in (1) is defined as

$$\mathrm{PAPR} = 10\log_{10} \frac{\max |x_t|^2}{E\left[|x_t|^2\right]}, \quad (2)$$

where $E[\cdot]$ denotes the expected value operation.

In the PTS approach, the input data $\mathbf{X}$ is partitioned into smaller V non-overlapping subblocks $\mathbf{X}_v \, (0 \le v \le V-1)$ with the same number of subcarriers such that

$$\mathbf{X} = \sum_{v=0}^{V-1} \mathbf{X}_v. \quad (3)$$

The partitioned subblocks are then transformed into V time-domain partial transmit sequences using N-point inverse fast Fourier transform (IFFT). Since the IFFT is a linear transformation, the representation of the block in time domain can be expressed as

$$\mathbf{x} = \mathrm{IFFT}\left\{\sum_{v=0}^{V-1} \mathbf{X}_v\right\} = \sum_{v=0}^{V-1} \mathrm{IFFT}\{\mathbf{X}_v\} \equiv \sum_{v=0}^{V-1} \mathbf{x}_v. \quad (4)$$

Next, the time domain sequences are independently rotated by phase factors $\Phi = [\phi_0 \, \phi_1 \, \cdots \, \phi_{V-1}]^T$ to produce a PAR-reduced OFDM signal

$$\mathbf{x}'(\Phi) = \sum_{v=0}^{V-1} e^{j\phi_v} \mathbf{x}_v. \quad (5)$$

The objective of the PTS scheme is to search for an optimal phase factor that yields the transmit signal with the minimum PAPR. Accordingly, we can state the optimization problem of the PTS scheme as

$$\begin{aligned} &\text{minimize} \quad && \max \left|\mathbf{x}'(\Phi)\right| \\ &\text{subject to} \quad && 0 \le \phi_v < 2\pi, \quad v = 0, 1, \cdots, V-1. \end{aligned} \quad (6)$$

It is obvious that finding a best phase factor set is a complex and difficult problem; therefore, in the next section, we propose a novel implementation of the PTS scheme based on the EM method.

III. A NEW PTS SCHEME USING THE EM METHOD

A. The EM Optimization Algorithm

The Electromagnetism-like Method (EM) developed by Birbil and Fang [21] is a population-based stochastic global optimization method inspired by the Coulomb's Law of the electromagnetism theory. The EM method starts with an initial solution set (particles), and an attraction-repulsion mechanism is then used iteratively to move those particles towards optimality. The general scheme for the EM method is shown in Algorithm 1, which consists of four main procedures: *initialization*, *local search*, *calculation of the total force*, and *movement of the particles*, respectively. These procedures are interpreted as follows. The first procedure, *initialization*, is used to sample M points (particles) [2] randomly from the feasible region. The next procedure, *local search*, is a neighborhood search procedure which can be applied to one or many points for local refinement to get better solutions at each iteration. The total force exerted on each point by all other points is calculated in the *calculation of the total force* procedure. The remaining procedure of the EM algorithm is the *movement of the particles* procedure, which is used for moving the sample points along the direction of the total force. For a more in-depth discussion on the EM method, the reader is referred to [21].

ALGORITHM 1 Electromagnetism-like Algorithm

```
1:  Initialize()
2:  while termination criteria are not satisfied do
3:     Local search()
4:     Calculation of the total force()
5:     Movement of the particles()
6:  end while
```

B. The EM Optimization Algorithm

In principle, the EM algorithm is a population-based search method in which a set of potential solutions (particles) to the problem is evolved. At iteration k, a population with M particles is generated. Each solution particle is considered as a particle in a multidimensional solution space with a certain charge. This charge is related to the objective function values associated with all the solution particles. The population is evolved by utilizing an attraction-repulsion mechanism to move sample particles towards optimality. In the following, we employ the EM method to search the optimal phase factor for the PTS technique in order to reduce the PAPR. The procedure of the proposed EM-based PTS can be described as follows:

[2] The words particle and point are interchangeably used.

- **Step 1)** Initialize the particle population at $k=0$: Like most stochastic algorithms, the EM method starts with generating M random sample particles $\left\{\left\{\theta_{m,v}^k\right\}_{v=1}^V\right\}_{m=1}^M$ from the feasible region, where V is the dimension of the problem (i.e., the number of subblocks) and $\theta_{m,v}^k$ denotes the vth coordinate of the particle m of the population at iteration k. Analogous to electromagnetism, each particle $\mathbf{\Theta}_m^k=\left\{\theta_{m,v}^k\right\}_{v=1}^V$ is regarded as a virtually charged particle that is released in the space. It should be noted that in a multi-dimensional solution space where each particle represents a solution, a charge is associated with each particle. As such, each coordinate of a particle, denoted as $\theta_{m,v}^k$, is computed by

$$\theta_{m,v}^k=l_v+\lambda\left(u_v-l_v\right), \tag{7}$$

where u_v is the upper bound of the vth dimension; l_v is the lower bound of the vth dimension; and λ is a uniform random number generator within $[0,1]$. As we are interested in the values of phase factors in the range of 0 to 2π, the upper bound and lower bound are set to 0 and 2π, respectively. Therefore, the range of phase factor will be bounded at $[0,2\pi)$. Meanwhile, since λ is a uniform random number generator within $[0,1]$, the distribution of phase factor is uniform distribution with $[0,2\pi)$. After a particle is sampled from the space, the objective function value for the particle is calculated. Given a particle (i.e., phase factor vector) $\mathbf{\Theta}_m^k$, the fitness function, defined as the amount of PAPR reduction, can be expressed as

$$f\left(\mathbf{\Theta}_m^k\right)=10\log_{10}\frac{\max\left|\mathbf{x}'\left(\mathbf{\Theta}_m^k\right)\right|^2}{E\left[\left|\mathbf{x}'\left(\mathbf{\Theta}_m^k\right)\right|^2\right]}. \tag{8}$$

When the M particles are all identified, the particle with the best objective function value is stored into $\mathbf{\Theta}_{best}^k=\left\{\theta_{best,v}\right\}_{v=1}^V$.

- **Step 2)** Local search: Local search is used to gather the neighborhood information for a sampled particle, which can be applied to one particle or to all particles in the population for local refinement at each iteration. Theoretically, the local search is expected to find a better solution especially when it is applied to all particles. However, the local search is usually time-consuming. Therefore, in this study, the EM algorithm is implemented with local search on the current better particle. The procedure of the local search can be described as follows:
- **Step 2.1)** Calculate maximum feasible random step length $s_{\max}$: First, the length is calculated by the maximum difference of each dimension's upper and lower bound. Since the upper and lower bound of each dimension is 2π and 0, respectively, the maximum difference of each dimension's upper and lower bound is 2π. Second, it makes use of the parameter $\delta\in[0,1]$ to have a feasible random length. Therefore, the maximum feasible step length can be computed using the following equation:

$$s_{\max}=\delta\left(\max_{1\le v\le V}\left(u_v-l_v\right)\right). \tag{9}$$

- **Step 2.2)** Generate a candidate of particle $\breve{\mathbf{\Theta}}=\left\{\breve{\theta}_v\right\}_{v=1}^V$: A new particle $\breve{\mathbf{\Theta}}$ is generated from the current best particle $\mathbf{\Theta}_{best}^k$. As $\breve{\mathbf{\Theta}}$ is a small random change coming from $\mathbf{\Theta}_{best}^k$, here, we randomly change two coordinates to generate $\breve{\mathbf{\Theta}}$, where the modified coordinate of the current best particle, denoted as $\breve{\theta}_v$, is computed using the following equation:

$$\breve{\theta}_v=\theta_{best,v}^k+\lambda\cdot s_{\max}. \tag{10}$$

- **Step 2.3)** Decide whether to update the current best particle $\mathbf{\Theta}_{best}^k$: If the new particle $\breve{\mathbf{\Theta}}$ observes a better particle, the sample particle $\mathbf{\Theta}_{best}^k$ is replaced by this new particle $\breve{\mathbf{\Theta}}$.
- **Step 2.4)** Repeat Step 2.1 to Step 2.3 until the maximum number of local search iteration is met.
- **Step 3)** Calculation of the total force: In this procedure, an artificial electromagnetism field is built to propel the particles to new positions via the Coulomb's law of the electromagnetism theory. The artificial charge q_m^k at particle $\mathbf{\Theta}_m^k$ is determined by the fitness function value, and is calculated using the following equation:

$$q_m^k=\exp\left\{-V\frac{f\left(\mathbf{\Theta}_m^k\right)-f\left(\mathbf{\Theta}_{best}^k\right)}{\sum_{m=1}^M\left[f\left(\mathbf{\Theta}_m^k\right)-f\left(\mathbf{\Theta}_{best}^k\right)\right]}\right\}. \tag{11}$$

By observing (11), we can find that 1) a large $f\left(\mathbf{\Theta}_m^k\right)$ results in a small q_m^k, and vice versa; and 2) the artificial charges are all positive. Now, the problem on hand is how to determine the force of attraction or repulsion between each pair of particles $\mathbf{\Theta}_m^k$ and $\mathbf{\Theta}_r^k$. Suppose that $f\left(\mathbf{\Theta}_m^k\right)<f\left(\mathbf{\Theta}_r^k\right)$, which implies that $q_m^k>q_r^k$, in this case the one that has better fitness function value is preferred, that is, $\mathbf{\Theta}_m^k$ is the preferred particle and particle $\mathbf{\Theta}_r^k$ should be "attracted" to particle $\mathbf{\Theta}_m^k$. That means the particle attracts other particles with better fitness function values and repels other particles with fitness cost function values. After determining the charge of each particle on $\left\{\mathbf{\Theta}_m^k\right\}_{m=1}^M$ and defining the rule of attraction-repulsion mechanism of artificial charge, the force vector, $\mathbf{F}_{m,r}^k$, between two particles $\mathbf{\Theta}_m^k$ and $\mathbf{\Theta}_r^k$, is computed as

$$\mathbf{F}_{m,r}^{k}=\begin{cases}\left(q_r^k-q_m^k\right)\frac{q_r^k\cdot q_m^k}{\left\|q_r^k-q_m^k\right\|^2}, & \text{if} \quad f\left(\boldsymbol{\Theta}_r^k\right)<f\left(\boldsymbol{\Theta}_m^k\right) \quad \text{(attraction)}\\ \left(q_m^k-q_r^k\right)\frac{q_r^k\cdot q_m^k}{\left\|q_r^k-q_m^k\right\|^2}, & \text{if} \quad f\left(\boldsymbol{\Theta}_r^k\right)\geq f\left(\boldsymbol{\Theta}_m^k\right) \quad \text{(repulsion)}\end{cases} \tag{12}$$

The total force $\boldsymbol{\Xi}_m^k=\left[\wp_{m,1}^k \quad \wp_{m,2}^k \quad \cdots \quad \wp_{m,V}^k\right]^T$ exerted on each particle $\boldsymbol{\Theta}_m^k$ by the other $(M-1)$ particles is then calculated by

$$\boldsymbol{\Xi}_m^k=\sum_{\substack{r=1\\ r\neq m}}^{M}\mathbf{F}_{m,r}^k,\quad m=1,2,\cdots,M. \tag{13}$$

- **Step 4)** Movement of the particles: After calculating the total force $\boldsymbol{\Xi}_m^k$, the particle m is updated in v th coordinate of the force by a random step length as given as

$$\theta_{m,v}^{k+1}=\begin{cases}\theta_{m,v}^k+\lambda\frac{\wp_{m,v}^k}{\left\|\boldsymbol{\Xi}_m^k\right\|}\left(u_v-\theta_{m,v}^k\right), & \text{if} \quad \wp_{m,v}^k>0\\ \theta_{m,v}^k+\lambda\frac{\wp_{m,v}^k}{\left\|\boldsymbol{\Xi}_m^k\right\|}\left(\theta_{m,v}^k-l_v\right), & \text{if} \quad \wp_{m,v}^k\leq 0\end{cases} \tag{14}$$

- **Step 5)** Repeat Step 2 to Step 4 for $k=k+1$ until the maximum number of iteration is met.

C. Complexity Comparison for Finding Suboptimal Solutions

As SA, CE, PSO, and the EM are all population-based search methods, we may therefore fix the number of samples, Sam, to find the suboptimal solutions with low complexity. In this case, the complexity for SA, CE, PSO, and the EM method can further be expressed in term of the number of samples, where each sample is calculated using the N- point IFFT. Accordingly, the number of samples for SA, CE, PSO, and the EM are $MAXITER$, $pop\times MAXITER$, $pop\times MAXITER$, and $(pop+LSITER)\times MAXITER$, respectively, where $MAXITER$ is the maximum number of iterations, pop is the number of sample points (particles), and $LSITER$ is the maximum number of local search iterations. It should be noted that the complexity for each sample to find a suboptimal solution is $\mathcal{O}(N\log N)$ multiplications.

IV. Numerical Results

Simulation experiments are conducted in this section to verify the PAPR performance of the proposed EM method presented in Section III for OFDM systems. In the simulations, the numbers of subcarriers are set to be $N = 64$ and $N = 128$ subcarriers, respectively, which are divided into $V=8$ subblocks, and data symbols are modulated using the QPSK constellation with four times oversampling (i.e., $P=4$). The criteria for performance measurement considered here are the complementary cumulative distribution function $(\mathrm{CCDF}=\Pr[\mathrm{PAPR}>\mathrm{PAPR}_0])$ of the PAPR and the average PAPR performance, where the CCDF is the probability that the PAPR of a symbol exceeds the threshold level PAPR_0. In order to generate the CCDF of the PAPR, 10,000 OFDM blocks are generated randomly. For comparison, we also tested some existing stochastic optimization-based approaches for PAPR reduction, including the SA algorithm [15][16], the CE method [18], and PSO [19][20].

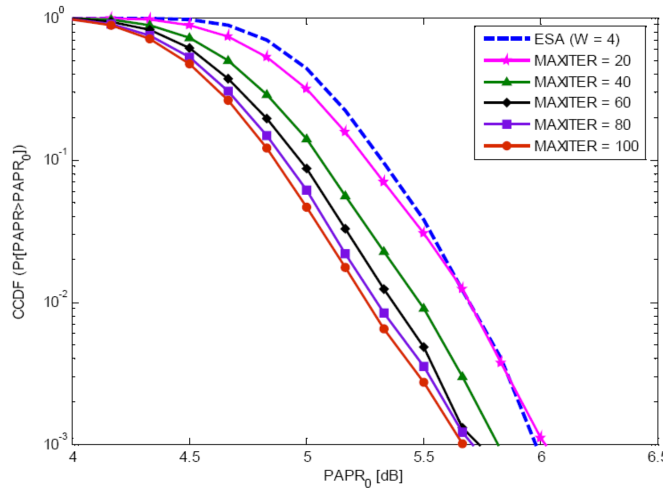

Fig. 1. Comparison of the PAPR CCDF of the different numbers of the maximum number of iterations of the EM method for *N* =64.

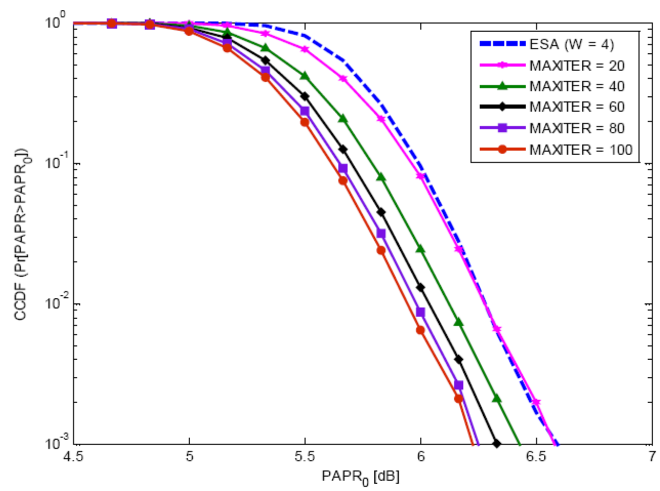

Fig. 2. Comparison of the PAPR CCDF of the different numbers of the maximum number of iterations of the EM method for *N* =128.

Figs. 1 and 2 show the variation in CCDF with the proposed EM method for different numbers of the maximum number of iterations, $MAXITER$, with $N=64$ and $N=128$, respectively. In the EM method, the population size is assumed to be $pop=20$; the maximum number of local search iterations is $LSITER=10$; and the corresponding maximum number of iterations are $MAXITER=20$, 40, 60, 80, and 100, respectively. In addition, we selected the exhaustive search algorithm (ESA) mentioned in [3] to compare the performance of PAPR reduction with that of the EM searching method. In the ESA, the selection of the phase factors was limited to a set of finite number of elements W. The ESA was then employed to find the best phase factor. Here, four allowed phase factors $+1$, -1, $+j$, and $-j$

$(W = 4)$ were used for the ESA, and the PAPR reduction performance was obtained by a Monte Carlo search with a full enumeration of $W^V(4^8 = 65,536)$ phase factors. As shown in Figs. 1 and 2, as the maximum number of iterations was increased, and the CCDF of the PAPR has been improved. When $\Pr[\mathrm{PAPR} > \mathrm{PAPR}_0] = 10^{-3}$, we can see that the performance of the proposed EM method provides an approximate PAPR reduction as with that of the conventional ESA. When $\Pr[\mathrm{PAPR} > \mathrm{PAPR}_0] = 10^{-3}$, it is found in Table I that the proposed EM method not only achieves an improvement of 0.11-0.31 dB in PAPR reduction for different scenarios than the ESA but also has a much lower computational complexity than the ESA.

TABLE I
COMPARISONS OF THE PAPR PERFORMANCE OF THE VARIOUS MAXIMUM NUMBER OF ITERATIONS OF THE PROPOSED EM METHOD AND THE ESA WITH $N = 64$ AND $N = 128$, RESPECTIVELY, AT $\Pr[\mathrm{PAPR} > \mathrm{PAPR}_0] = 10^{-3}$

Method	Number of subcarriers	Amount computation	Performance (PAPR 0.001)
ESA	64	65,536	5.98dB
EM	64	$30 \times 20 = 600$	6.03dB
EM	64	$30 \times 40 = 1,200$	5.82dB
EM	64	$30 \times 60 = 1,800$	5.74dB
EM	64	$30 \times 80 = 2,400$	5.72dB
EM	64	$30 \times 100 = 3,000$	5.67dB
ESA	128	65,536	6.54dB
EM	128	$30 \times 20 = 600$	6.62dB
EM	128	$30 \times 40 = 1,200$	6.43dB
EM	128	$30 \times 60 = 1,800$	6.33dB
EM	128	$30 \times 80 = 2,400$	6.26dB
EM	128	$30 \times 100 = 3,000$	6.23dB

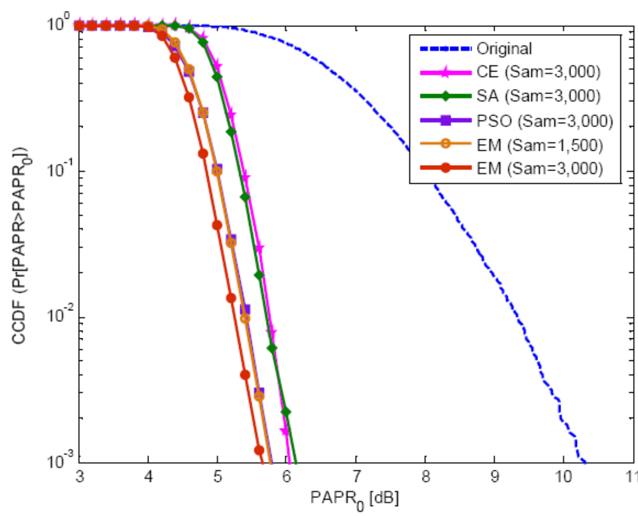

Fig. 3. Comparison of the PAPR CCDF of CE, SA, PSO, and the proposed EM for $N = 64$ and QPSK modulation.

Next, we compared the proposed EM-based PTS scheme with other existing stochastic optimization-based PTS approaches for the *same* number of samples, $Sam = 3,000$. Figs. 3 and 4 show the CCDFs of the PAPR of the OFDM system using the SA, the CE method, PSO, the proposed EM method, and the original OFDM with the number of subcarriers $N = 64$ and $N = 128$, respectively, where the original OFDM was directly obtained from the output of the IFFT operation and the simulation parameters for various stochastic optimization-based approaches given in Table II. It can be seen that the PAPR of the original OFDM signal at $\Pr[\mathrm{PAPR} > \mathrm{PAPR}_0] = 10^{-3}$ for $N = 64$ and $N = 128$ is 10.31 and 10.56 dB, respectively, which indicates a large PAPR. For $N = 64$, the suppressed PAPRs of the SA, the CE method, PSO, and the proposed EM method at $\Pr[\mathrm{PAPR} > \mathrm{PAPR}_0] = 10^{-3}$ are 6.14, 6.04, 5.78, and 5.67 dB, respectively. For $N = 128$, the PAPRs of the CE method, the SA, PSO, and the proposed EM method at $\Pr[\mathrm{PAPR} > \mathrm{PAPR}_0] = 10^{-3}$ are reduced to 6.69, 6.63, 6.40, and 6.23 dB, respectively. With the same complexity, Figures 3 and 4 show the superiority of our proposed EM-based PTS scheme. By decreasing the complexity, the proposed EM method with $Sam = 1,500$ obtains almost the same PAPR reduction as that of the PSO with $Sam = 3,000$. This means PSO requires more samples (i.e., higher complexity) to obtain the same PAPR reduction performance as the proposed EM method. Therefore, the proposed EM method can offer better PAPR reduction while keeping a low complexity.

TABLE II
SIMULATION PARAMETERS FOR THE SA, THE CE METHOD, PSO, AND THE PROPOSED EM METHOD

Method	Population size	Number of iteration	Number of local search	Amount computation
SA	1	3,000		3,000
CE	200	15		3,000
PSO	30	100		3,000
EM	20	50	10	1,500
EM	20	100	10	3,000

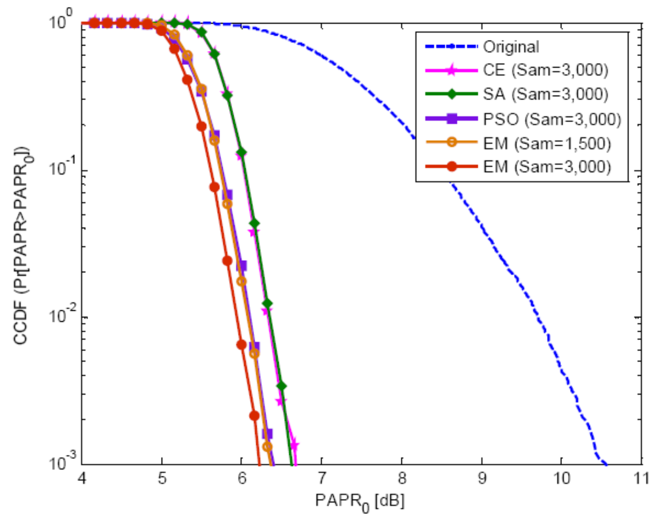

Fig. 4. Comparison of the PAPR CCDF of CE, SA, PSO, and the proposed EM for $N = 128$ and QPSK modulation.

Lastly, a fair comparison of the performance-complexity tradeoffs for the different stochastic PTS searching strategies with $N = 64$ and $N = 128$, respectively, is provided in Fig. 5, where the **average** PAPR reduction is the function of the number of sample. It can be seen that 1) it is beneficial to select more samples so that the average PAPR reduction performance can be improved; 2) as the number of sample becomes greater than 1,200, the figure illustrates that the EM method leads to a much smaller average PAPR than the other stochastic methods; and 3) the application of the EM method to solve the optimum phase searching problem of PTS yields an enhanced tradeoff in the low average PAPR range about 4.77 and 5.54 dB for $N = 64$ and $N = 128$, respectively.

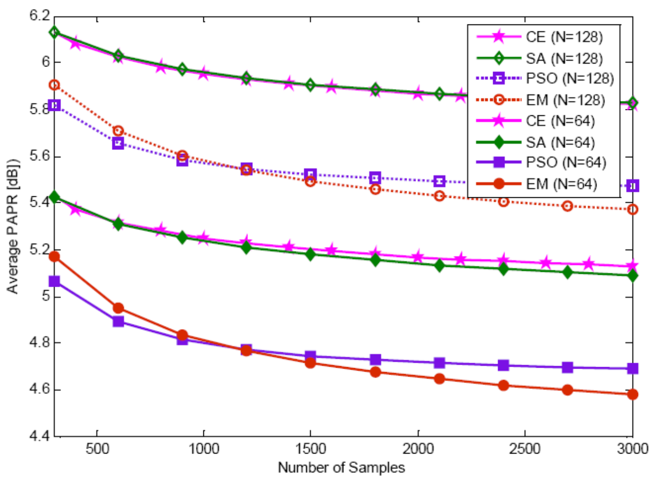

Fig. 5. Average PAPR reduction comparison of CE, SA, PSO, and the proposed EM for the same complexity with $N = 64$, $N = 128$, and QPSK modulation.

V. Conclusions

This paper presented an EM-based method that was used to obtain the optimal phase factor for the PTS technique to reduce computational complexity and improve PAPR performance. We formulated the phase factor search of the PTS technique as a global optimization problem with bound constraints. We then applied the EM-based method to search for the optimal phase factor. The computer simulation results showed that compared with the various stochastic search techniques developed previously, the proposed EM method obtained the desirable PAPR reduction with low computational complexity.

References

[1] S. H. Han and J. H. Lee, "An overview of peak-to-average power ratio reduction techniques for multicarrier transmission," *IEEE Wireless Commun. Mag*., vol. 12, no. 2, pp. 56-65, 2005.

[2] T. Jiang and Y. Wu, "An overview: peak-to-average power ratio reduction techniques for OFDM signals," *IEEE Trans. Broadcast.*, vol. 54, no. 2, pp. 257-268, June 2008.

[3] S. H. Muller and J. B. Huber, "OFDM with reduced peak-to-average power ratio by optimum combination of partial transmit sequences," *IEE Electron. Lett.*, vol. 33, no. 5, pp. 368-369, Feb. 1997.

[4] X. Zhu, T. Jiang, and G. Zhu, "Novel schemes based on greedy algorithm for papr reduction in OFDM systems," *IEEE Trans. Consum. Electron.*, vol. 54, no. 3, pp. 1048-1052, Aug. 2008.

[5] N. T. Hieu, S.-W. Kiom, and H.-G. Ryu, "PAPR reduction of the low complexity phase weighting method in OFDM communication system," *IEEE Trans. Consum. Electron.*, vol. 51, no. 3, pp. 776-782, Aug. 2005.

[6] A. Bo, Z. Yang, C. Pan, T. Zhang, and J. Ge, "Effects of PAPR reduction on HPA predistortion," *IEEE Trans. Consum. Electron.*, vol. 51, no. 4, pp. 1143-1147, Nov. 2005.

[7] D.-H. Park and H.-K. Song, "A New PAPR reduction technique of OFDM system with nonlinear high power amplifier," *IEEE Trans. Consum. Electron.*, vol. 53, no. 2, pp. 327-332, May 2007.

[8] J. Wang, B. Liu, and X. Zhou, "PCE algorithm for PAPR reduction in OFDM-ROF system," *IEEE Trans. Consum. Electron.*, vol. 55, no. 3, pp. 1078-1082, Aug. 2009.

[9] J. Wang, Y. Guo, and X. Zhou, "PTS-clipping method to reduce the PAPR in ROF-OFDM system," *IEEE Trans. Consum. Electron.*, vol. 55, no. 2, pp. 356-359, May 2009.

[10] S. Cha, M. Park, S. Lee, K.-J. Bang, and D. Hong, "A new PAPR reduction technique for OFDM systems using advanced peak windowing method," *IEEE Trans. Consum. Electron.*, vol. 54, no. 2, pp. 405-410, May 2008.

[11] Y. Hou and Y. Hase, "New OFDM structure with parallel combinatory code," *IEEE Trans. Consum. Electron.*, vol. 55, no. 4, pp. 1854-1859, Nov. 2009.

[12] J. Wang, X. Zhou, Y. Xu, and W. Wang, "Performance improvement of OFDM-ROF system with clipping and filtering technique," *IEEE Trans. Consum. Electron.*, vol. 54, no. 2, pp. 296-299, May 2008.

[13] J. Yang, L. Chen, Q. Liu, and D. Chen, "A modified selected mapping technique to reduce the peak-to-average power ratio of OFDM signals," *IEEE Trans. Consum. Electron.*, vol. 53, no. 3, pp. 846-851, Aug. 2007.

[14] K. D. Choe, S. C. Kim, and S. K. Park, "Pre-scrambling method for PAPR reduction in OFDM communication systems," *IEEE Trans. Consum. Electron.*, vol. 50, no. 4, pp. 1044-1048, Nov. 2004.

[15] T. Jiang, W. Xiang, P. C. Richardson, J. Guo, and G. Zhu, "PAPR reduction of OFDM signals using partial transmit sequences with low computational complexity," *IEEE Trans. Broadcast*., vol. 53, no. 3, pp. 719-724, Sept. 2007.

[16] T. Nguyen and L. Lampe, "PAPR reduction of OFDM signals using partial transmit sequences with low computational complexity," *IEEE Trans. Wireless Commun*., vol. 7, no. 2, pp. 746-755, Feb. 2008.

[17] L. Wang and C. Tellambura, "Cross-entropy-based sign-selection algorithms for peak-to-average power ratio reduction of OFDM systems," *IEEE Trans. Signal Process.*, vol. 56, no. 10, pp. 4990-4994, Oct. 2008.

[18] J.-C. Chen, "Partial transmit sequences for peak-to-average power ratio reduction of OFDM Signals with the cross-entropy method," *IEEE Signal Process. Lett.*, vol. 16, no. 6, pp. 545-548, June 2009.

[19] J.-H. Wen, S.-H. Lee, Y.-F. Huang, and H.-L. Hung, "A sub-optimal PTS algorithm based on particle swarm optimization technique for PAPR reduction in OFDM Systems," *EURASIP J. Wireless Commun. Netw.*, vol. 2008, article ID 601346, May 2008.

[20] H-L. Hung, Y.-F. Huang, C.-M. Yeh, and T.-H. Tan, "Performance of particle swarm optimization techniques on PAPR reduction for OFDM Systems," in *Proc. IEEE Int. Conf. Syst., Man, Cybern*, 2008, pp. 2390-2395.

[21] S.I. Birbil and S.-C. Fang, "An electromagnetism-like mechanism for global optimization," *J. Glob. Opt.*, vol. 25, no. 3, 263-282, 2003.

[22] S. I. Birbil, S.-C. Fang, and R.-L. Sheu, "On the convergence of a population - based global optimization algorithm," *J. Glob. Opt.*, vol. 30, no. 2, 301-318, 2004.

Biographies

Jung-Chieh Chen (S'02-M'05) received a B.S. degree in Electrical Engineering from the Tatung Institute of Technology, Taipei, Taiwan, his M.S. degree in Electrical Engineering from National Chung Cheng University, Chiayi, Taiwan, and a Ph.D. degree in Communications Engineering from National Tsing Hua University, Hsinchu, Taiwan. Since August 2005, he has been with the Department of Optoelectronics and Communication Engineering, National Kaohsiung Normal University, Kaohsiung, Taiwan, where he became an Associate Professor in March 2009. His research interests include wireless communication systems, radio resource management, digital communication hardware implementation, radiolocation techniques, the stochastic optimization method, and graphical approach for information processing.