RBF Neural Network Based SLM Peak-to-Average Power Ratio Reduction in OFDM Systems

Insoo Sohn

ABSTRACT—One of the major disadvantages of the orthogonal frequency division multiplexing system is high peak-to-average power ratio (PAPR). Selected mapping (SLM) is an efficient distortionless PAPR reduction scheme which selects the minimum PAPR sequence from a group of independent phase rotated sequences. However, the SLM requires explicit side information and a large number of IFFT operations. In this letter we investigate a novel PAPR reduction method based on the radial basis function network and SLM.

Keywords—PAPR reduction, OFDM system.

I. Introduction

To provide a high data rate and reliable communications for next generation mobile communication systems, orthogonal frequency division multiplexing (OFDM) is an effective technique. However, one major disadvantage of the OFDM system is that the transmitted signal has a high peak-to-average power ratio (PAPR). These large peaks will occasionally reach the power amplifier saturation region, resulting in signal distortion. Highly linear power amplifiers, at the expense of increased cost of the OFDM system, are thus required to mitigate this effect.

Among many PAPR reduction schemes that have been proposed, selected mapping (SLM) [1] is an efficient distortionless scheme which selects the minimum PAPR sequence from a group of independent phase rotated sequences with different PAPRs. The main disadvantage of the SLM scheme is that the selection information is required at the receiver. Previous work on using the SLM scheme without explicit side information has been proposed [2], but this scheme still suffers some rate loss in that it requires concatenation of label information to the original information blocks. Furthermore, the modified SLM scheme with label insertion still requires V number of IDFT modules in the transmitter, where V is the number of phase rotated sequences. The Hopfield neural network (HNN) is a type of multilayer perceptron which is an effective nonlinear signal processing tool in solving combinatorial optimization problems [3]. However, HNN suffers from slow convergence and unpredictable solutions during the training stage due to its slow steepest-descent based back-propagation algorithm with complex multilayer architecture [4]. Recently, a new PAPR reduction scheme based on an optimized HNN without any training stage or back-propagation algorithm was proposed in [5], with great performance results. In this letter, we propose using the radial basis function network (RBFN) which was introduced in 1988 as a multivariate interpolator [6]. The RBFN model is one of the most commonly used neural network models and has been applied successfully in areas such as channel equalization [7]. Furthermore, RBFN has a simple network structure and computational complexity compared to the HNN [4]. The proposed scheme provides the optimal mapping of the OFDM signal based on the RBFN-optimized SLM generated sequences, reducing the PAPR substantially.

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Insoo Sohn (phone: + 82 2 2260 8604, email: isohn@dongguk.edu) is with Department of Electronic Engineering, Dongguk University, Seoul, Korea.

II. PAPR Reduction

1. Selected Mapping Scheme

The main idea of the SLM scheme is to choose one particular signal with the lowest PAPR (but retaining the original information) from diversely mapped signals. Defining

$\mathbf{P}^{(v)} = \left[P_1^v, P_2^v, \cdots, P_N^v\right]$ as a phase rotation vector, where N is the number of subcarriers and $P_n^v = e^{j\varphi_n^v}$, $e^{j\varphi_n^v} \in [0, 2\pi)$, $n = 1, \cdots, N$, and $v = 1, \cdots, V$, we can map the OFDM block into V mapped OFDM blocks with different phase rotations. Then, one OFDM block is selected out of V candidates, namely, the one with the lowest PAPR in the time-domain.

2. RBF Neural Network

An RBF neural network (RBFN) consists of three basic layers: the input layer, the hidden layer, and the output layer. The transformation from the input space to the hidden-unit space is nonlinear, whereas the mapping from the hidden-unit space to the output space is linear. The general architecture of the RBF neural network is represented by

$$F(\mathbf{x}) = \sum_{i=1}^{M} w_i \Phi(\|\mathbf{x} - \mathbf{c}_i\|), \tag{1}$$

where $\mathbf{x}$ is the input data vector, M is the total number of RBFs, w_i denotes the weights of the output layer, $\Phi(\bullet)$ is the Gaussian basis function, and $\{\mathbf{c}_i\}$ denotes the centers of RBFs. The hidden layer's activation functions modify themselves slowly according to a nonlinear optimization method [8]. As for the output layer, the weights evolve rapidly through a linear optimization strategy.

3. RBFN-SLM Scheme

Our proposed RBFN-based PAPR reduction scheme is shown in Fig. 1. As shown in the figure, the RBFN-SLM module consists of two main parts. The RBFN phase rotation selector selects the optimum phase rotation vector to be applied to the current OFDM block and provides the optimum phase rotation vector index to the SLM encoder. Using the optimum phase rotation vector index obtained in the RBFN phase rotation selector, the SLM encoder finds the corresponding phase rotation vector from its database and maps the input OFDM blocks to the new minimum PAPR-optimized OFDM blocks. The RBFN phase rotation selector is based on the RBFN architecture. Its design uses the Gaussian function as the basis function; the RBF centers are given by

$$\mathbf{c}_i = \left[e^{j\varphi_1}, e^{j\varphi_2}, \cdots, e^{j\varphi_N}\right], \tag{2}$$

where $\varphi_n \in [0, 2\pi)$, $n = 1, \cdots, N$, and $i = 1, \cdots, M$. To reduce the complexity of the RBFN phase rotation selector, the hidden layer's RBF centers are defined using the conventional SLM scheme's minimum PAPR phase rotation vectors without having to use complex nonlinear optimization training. After determining the RBF centers, the weights of the output layer are adapted using the LMS algorithm expressed as

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \alpha(F_k - d_k)\Phi(\mathbf{x}_k), \tag{3}$$

where α is the learning rate, F_k is the output of the RBFN phase rotation selector, d_k is the SLM minimum PAPR phase rotation index, and $\mathbf{x}_k$ is the test data vector. The SLM encoder maps the input OFDM block into

$$\mathbf{A}_{\tilde{u}} = \mathbf{A} \otimes \mathbf{P}_{\tilde{u}}, \tag{4}$$

where $\mathbf{A}_{\tilde{u}}$ is the minimum PAPR phase rotated sequence, $\mathbf{A}$ is the input OFDM sequence, $\mathbf{P}_{\tilde{u}}$ is the phase rotation vector, $\tilde{u} \in \{1, 2, \cdots, M\}$ is the optimum phase rotation vector index selected by the RBFN phase rotation selector, and $\otimes$ represents the component-wise multiplication. Note that the proposed scheme requires only a single IFFT operation and performs PAPR minimization without the complex minimum PAPR calculation procedure.

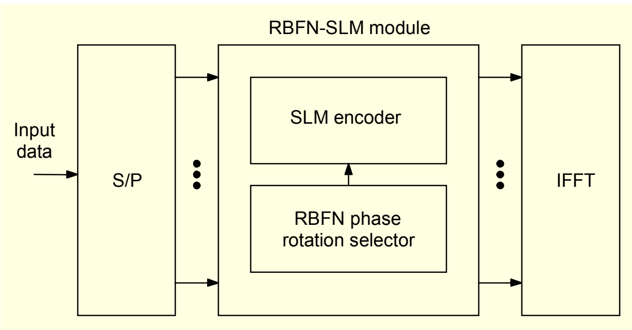

Fig. 1. Block diagram of the proposed PAPR reduction scheme.

III. Simulation Results

In this section, the simulation results of the proposed PAPR reduction scheme based on RBFN are presented. The data symbols are modulated using the QPSK constellation. The number of subcarriers is set to N = 128. The number of the RBFN phase rotation selector's hidden layer centers is set to M = 1024 using N dimensional statistically independent rotation sequences obtained from the conventional SLM scheme. The weights of the output layer are adapted using the LMS algorithm. Figure 2 shows some weights of the output layer adapting with the increasing number of iterations. Figure 2 demonstrates that the output layer weights of the RBFN phase rotation selector are able to converge fairly quickly at an iteration number approximately equal to 5000, which is also equal to the training period of the RBFN in the RBFN phase rotation selector. Figure 3 shows a PAPR performance comparison of the proposed RBFN-SLM, HNN, and conventional SLM methods. The complementary cumulative density function (CCDF) of the PAPR of the OFDM signals from each method is presented. In the SLM technique, 128 vectors of phase rotations from the set {±1, ±j} for each subcarrier are generated. The vector with the lowest PAPR value is selected for OFDM signal transmission. As for the HNN technique, the objective function proposed in [3] is used. As Fig. 3 demonstrates, the HNN method shows slightly better performance compared to the RBFN-SLM technique; however, the HNN PAPR reduction scheme's performance improvement is achieved at the expense of high complexity and difficult parameter setting problems. As for the proposed scheme, the PAPR performance is superior to the SLM method and shows similar performance to the HNN methods with much lower complexity.

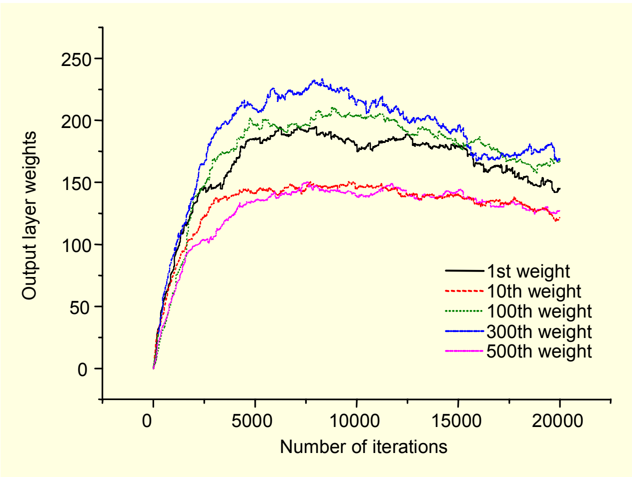

Fig. 2. Weights of the output layer of RBFN phase rotation selector.

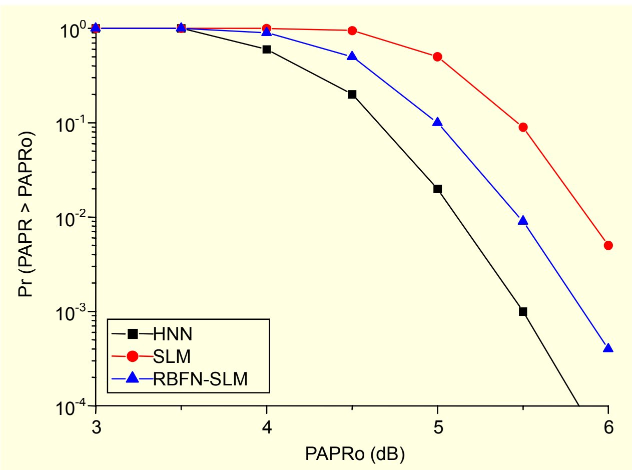

Fig. 3. CCDF of PAPR of QPSK-OFDM signals using RBFN-SLM, HNN, and SLM schemes with $N = 128$.

IV. Conclusion

In this letter, a novel PAPR reduction scheme using RBFN is proposed. The proposed RBFN-SLM technique is essentially an adaptive nonlinear OFDM signal mapper which reduces the PAPR substantially based on the optimum integration of SLM and RBFN methods. Compared to the conventional SLM and HNN PAPR reduction schemes, the proposed scheme shows a significant performance advantage with low computational complexity.

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