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Neural Network Based Joint Carrier Frequency Offset and Sampling frequency Offset Estimation and Compensation in MIMO OFDM-OQAM Systems.

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Abstract

A derivative of orthogonal frequency division multiplexing, (OFDM) based on offset quadrature amplitude modulation (OQAM), popularly known as OFDM-OQAM, is one of the dominant waveform contenders for 5th generation wireless communication systems. In this paper we investigate on channel estimation for OFDM-OQAM modulations in the case of multiple-input multiple-output (MIMO) transmissions over radio channels. We propose neural network (NN) based joint CFO and SFO estimation along with filter bank compensation in MIMO OFDM-OQAM systems. Here CFO and SFO ranges are evenly divided into a set of sub-ranges, which are being estimated using three layer NN based classifier and being supported by a dedicated CFO and SFO compensation unit. The performance evaluation shows that the proposed joint estimation and compensation technique gives the mean square error value (10^{-4}) even at a very low $SNR = 0\ dB$ with $N_T = 2$ and $N_R = 4$.

1 Introduction

Carrier frequency offset (CFO) and sampling frequency offset (SFO) are one of the most common impairments in wireless communication systems, which often occurs due to the oscillator frequency mismatch or Doppler shift and inaccurate synchronization and gain control for analog to digital conversion respectively. CFO mainly occurs due to the oscillator frequency mismatch or Doppler shift and SFO mainly occurs due to inaccurate synchronization and gain control for analog to digital conversion, preventing users from obtaining correct messages [1, 2].

Recently, several research has been carried out to mitigate the effect of CFO and SFO by virtue of estimating the CFO and SFO values [3, 4]. Further, in [5, 6] a joint estimation of CFO and SFO is presented. In [5], the joint ML based SFO and CFO estimator for orthogonal frequency division multiplexing (OFDM) systems is presented. In [6], a pilot-based ML joint estimation of CFO and SFO is proposed for multiuser OFDM with offset quadrature amplitude modulation (OQAM) systems, known as OFDM-OQAM, which has has attracted more and more attentions due to the good spectral characteristics and improved spectral efficiency [7]. Most of the CFO and SFO estimation techniques use either the ML based estimation or pilot based detection. However, ML based estimation suffers from high computation complexity, whereas pilot based estimation increase the symbol time frame duration of the transmitter [1]. Recently, research is being carried out in MIMO OFDM-OQAM systems focusing in the channel estimation issues [8, 9]. Thorough literature survey reveals that no work has been carried out till date addressing the CFO and SFO issues in MIMO OFDM-OQAM systems. However, the compensation of CFO and SFO values has a vital importance to maintain the orthogonality of the subcarrier in the frequency domain for MIMO OFDM-OQAM systems.

Nowadays machine learning is finding its importance in solving some complex problems and now has been applied to solve the problems incurred due to several imperfections in wireless communication system [10]. Neural networks (NNs) are a class of machine learning technique, which tries to imitate the human brain, are used to estimate the CFO owing to its simple structure [1, 11]. In [1], a NN based coarse CFO estimator is employed which has higher compatibility compared to traditional CFO estimators. In [11], NN for channel estimation and signal detection in OFDM systems is presented where first the channel state information (CSI) is estimated before detecting the transmitted signal. To the best of the authors' knowledge, the joint estimation and compensation of CFO and SFO using NN has not been reported so far.

In this paper, we propose a joint CFO and SFO estimation algorithm using NN based machine learning technique for MIMO OFDM-OQAM system. Next, two sequential filter banks are used to compensate the estimated CFO and SFO values. The main contribution of our work are as follows:

- A system model of MIMO OFDM-OQAM system with NN has been proposed.
- A three layer NN based classifier architecture is proposed to jointly estimate the CFO and SFO sub-ranges.
- Next, two filter banks are used in a sequential fashion (see in Fig. 3) to compensate the estimated CFO value followed by the compensation of the estimated SFO value.
- To show the efficacy of proposed NN based estimator, the slow fading channel environment has also been considered. Meanwhile, the testing results show that the proposed NN estimator has promising performance with an wide CFO and SFO acquisition range.

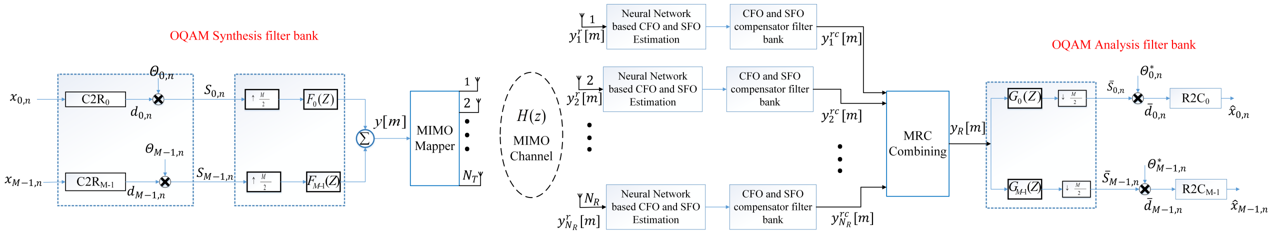

Figure 1. Proposed OFDM-OQAM System Architecture with Neural Network

2 System Model and Problem Formulation of Joint CFO and SFO

In this section, we first review the generic MIMO OFDM-OQAM system model as implemented in this work. In the first subsection, we present the essential modifications to the system model to estimate the CFO and SFO using the NN and compensate these imperfection through filter bank architecture as shown in Fig. 1. In the subsequent subsection, we have presented the problem formulation of joint CFO and SFO estimation in MIMO OFDM-OQAM systems.

2.1 Introduction to MIMO OFDM-OQAM System

The MIMO OFDM-OQAM system model, adopted in this work is shown in Fig. 1. The output signal of the OFDM-OQAM system is written as:

$$y[m] = \sum_n \sum_k \underbrace{\theta_{k,n} d_{k,n}}_{s_{k,n}} f_k \left[m - \frac{nK}{2}\right] e^{\frac{-j2\pi km}{N}}. \tag{1}$$

where $k \in 0,1,...,K-1$ is the subcarrier index, $n \in \mathbb{Z}$ is the symbol time index, $d_{k,n}$ is pair of OQAM real symbols, $s_{k,n} = d_{k,n}\theta_{k,n} = d_{k,n}e^{j\pi/2(k+n)}$ is OFDM- OQAM complex signal, a sequence $\theta_{k,n} = e^{j\pi/2(k+n)}$ is used to convert $d_{k,n}$ into complex signal, $f_k[m]$ is the finite impulse responses (FIR) of length M.

Next, the OFDM-OQAM signal is mapped to the MIMO transmission system to achieve the diversity gain. Spatial multiplexing of K data streams is performed at the transmitter using a precoding matrix P which is computed based on perfect channel state information at transmitter. Complex data symbol $f_k[m]$ is sent over each transmit antenna, with the precoding weight $P \in C^{N_R \times N_T}$. The equivalent channel, after precoding and propagation through the wireless MIMO channel is given by;

$$R_H = HP \tag{2}$$

where $H \in C^{N_R \times N_T}$ is the Rayleigh faded channel coefficient. The received signal over the N_R receive antennas is given by;

$$\begin{aligned}\mathbf{y^r}[m] &= (R_H * y[m-\tau_0])e^{\frac{j2\pi\Omega m}{M}} + \eta[m] \\ &= e^{\frac{j2\pi\Omega m}{M}} \left(\sum_{l=0}^{Q-1} h[l]y[m-l-\tau_0]\right) + \eta[m],\end{aligned} \tag{3}$$

where Q, τ_0 is the normalized STO with respect to one half of an OFDM-OQAM symbol duration, and Ω is the normalized CFO with respect to the subchannel frequency spacing, denoted as Δf. Finally, $\eta[m]$ represents the additive zero-mean white Gaussian noise.

2.2 Joint CFO and SFO estimation problem formulation

Consider an MIMO OFDM-OQAM system, where a received signal by N_{RF} antenna is given by;

$$\mathbf{y^r} = \Omega \mathbf{R_{H_\nu}} \mathbf{x} + \eta \tag{4}$$

Here, $\Omega \in C^{(N_{cfo}+N_{sfo})\times(N_{cfo}+N_{sfo})} = \mathrm{diag}(\omega)$ is the diagonal matrix with its diagonal elements corresponding to the joint CFO and SFO for the system as shown in Fig. 1. Here ω is the possible CFO and SFO value normalized by the OFDM-OQAM subcarrier spacing with $\omega \in [-0.5, 0.5]$, N_{cfo} is the number of possible CFO sub-ranges, N_{sfo} is the number of possible SFO subranges, and the superscript $[.]^T$ stands for the matrix transpose as described in [12]. Given the knowledge of Ω, joint frequency synchronization and detection in OFDM-OQAM systems could be conducted by minimizing the following Euclidean distance as $\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} ||\mathbf{y} - \Omega\mathbf{R_H}\mathbf{x}||^2$, here $||.||^2$ denotes the Euclidean norm.

3 Proposed NN based Joint CFO and SFO estimation and compensation in MIMO OFDM-OQAM

The received signal affected with CFO and SFO at each receive antenna, is given at the input to NN model that consists of one hidden layer. Further, the estimated value of CFO and SFO at each receive antenna are obtained even with a distorted received signal in terms of low SNR values.

3.1 Joint CFO and SFO estimation using NN

The neural network model is employed at the i^{th} receive antenna front end of the MIMO OFDM-OQAM receiver to estimate the CFO and SFO values, which may occur due to channel imperfection and ADC synchronization issues. The

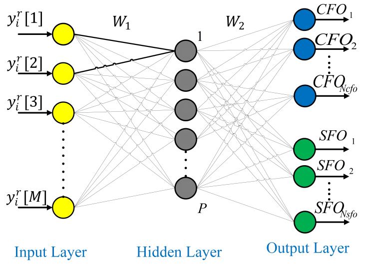

Figure 2. Neural Network Architecture for Joint CFO and SFO Estimation at i^{th} receive antenna

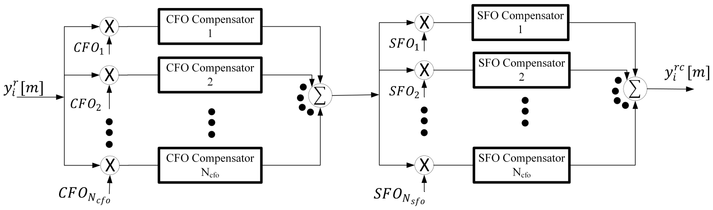

Figure 3. Proposed CFO and SFO compensator filter bank architecture for the receive signal at i^{th} antenna

NN contains a single hidden layer, as shown in Fig. 2. The received signal is fed to the NN input layer, therefore the number of input nodes is the vector length of the received signal (M). CFO and SFO values have been classified into $N_{CFO}+N_{SFO}$ classes, which are concatenated at the neural network output nodes, so there are $N_{CFO}+N_{SFO}$ nodes in the output layer. Further, the $softmax$ function is used as the activation function at the output layer's node and is given by;

$$f(a)=\frac{e^a}{\sum e^a}. \tag{5}$$

The hidden layer has $P=M/2$ number of nodes and the *sigmoid* function is used at the hidden node as the activation function, which is given as:

$$f(a)=\frac{1}{1+e^{-a}}. \tag{6}$$

Gradient based back propagation training algorithm is used to obtain the weights of NN. The size of the weight vectors are $W_1 \in C^{P\times M}$ and $W_2 \in C^{(N_{cfo}+N_{sfo})\times M}$. The output value of the each output node is $[0\ 1]$, showing the class of CFO and SFO which are further being compensated using filter bank architecture.

Considering the linear layer in Fig. 2 to be equivalent to a linear transform at the i^{th} receive antenna, and could be given by;

$$\mathbf{W}^{(1)}\mathbf{y_i^r}+\mathbf{b}^{(1)}=\Gamma\mathbf{y_i^r} \tag{7}$$

where Γ is the linear transform matrix with the same size as $\mathbf{W}^{(1)}$. Then, the input to the signal classifier is

$$\mathbf{y_i^r}^{(1)}=\Gamma\mathbf{y}=\Theta\Lambda\mathbf{s} \tag{8}$$

where,

$$\mathbf{s}=\mathbf{Fx};\ \Theta=\Gamma\Omega\mathbf{F}^H \tag{9}$$

The NN-based classifier is trained according to the maximum a-posterior probability. Assume s to be drawn from a finite set A=$s^{(1)},\cdots,s^{(N_{cfo}+N_{sfo})}$. After the offline training, the NN classify $\mathbf{y_i^r}^{(1)}$ to find the CFO and SFO value.

$$\mathbf{s}=\arg\max_{\mathbf{s}}\ p(\mathbf{s}|\mathbf{y_i^r}^{(1)}) \tag{10}$$

3.2 Proposed filter architecture for joint CFO and SFO compensation

In order to compensate the estimated range of a CFO and SFO at the i^{th} front end path the MIMO OFDM-OQAM receiver, a sequential structure of filter bank is designed, where first the CFO value is compensated followed by SFO compensation unit. The block diagram of the proposed filter bank architecture for the joint CFO and SFO compensation is presented in Fig. 3. Here first, the CFO of the received signal ($\mathbf{y_i^r}[m]$) is compensated with the dedicated CFO compensator filter which is selected by the output of NN. Next, the SFO of the received signal is compensated with the dedicated SFO compensator filter which is selected by the output of NN. The output of the compensator filter bank could be given by;

$$\mathbf{y_i^{rc}}[m]=\left\{\mathbf{y_i^r}[m]\begin{bmatrix}CFO_1\\CFO_2\\\vdots\\CFO_{N_{cfo}}\end{bmatrix}e^{\frac{-j2\pi\Omega m}{M}}\right\}\begin{bmatrix}SFO_1\\SFO_2\\\vdots\\SFO_{N_{sfo}}\end{bmatrix}e^{\frac{-j2\pi\tau_0 m}{M}}. \tag{11}$$

Further, $y_R[m]$ is by doing MRC combining of $\{\mathbf{y_i^{rc}}[m]\}_{i=1}^{N_R}$. Next, $y_R[m]$ is demodulated to obtain the transmitted signal. The pseudo code of the proposed joint CFO and SFO detection using NN based estimator and compensation using filter bank unit is presented in Algorithm 1.

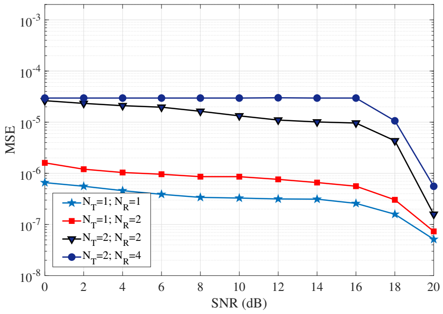

Figure 4. Mean square error plot

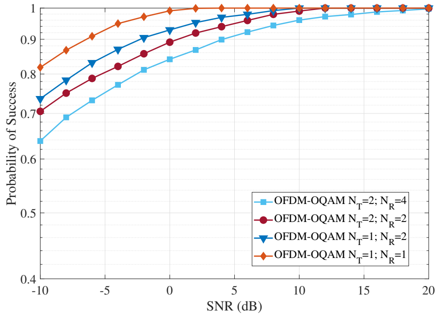

Figure 5. Probability of success vs. SNR plot for the NN based joint estimation technique

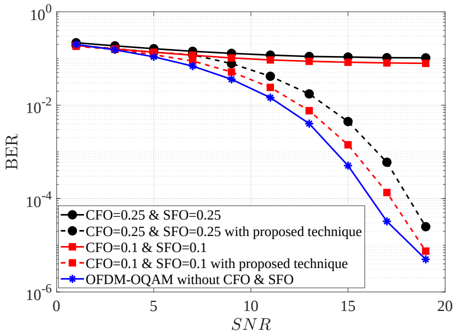

Figure 6. BER vs. SNR plot; $N_T=1$ and $N_R=2$

Algorithm 1 Pseudo code for proposed combining scheme at FC

```
Start;
for $i = 1 : N_R$ do
    Train the NN with high SNR $\bar{y}[m]$ with known CFO and SFO imperfection values.
    Classify the CFO and SFO value present in $\bar{y}[m]$
    Get the compensated received signal $\bar{y}_1[m]$ using (11).
Do the MRC combining of the compensated receive signal $y_R[m] = \frac{1}{||H||^2}\bar{y}_i[m], \quad i \in [1,2\cdots,N_R]$
Perform the OFDM-OQAM demodulation on $y_R[m]$.
End
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4 Simulation Results and Discussion

In order to evaluate the performance of the proposed scheme, we consider MIMO OFDM-OQAM systems with CFO and SFO imperfection. An extensive MATLAB simulation is carried out on a system having 8 GB RAM, i5 processor. It is assumed that the each receive antenna receiver may experience an independent CFO, SFO is value. Mean-squared error (MSE) evaluations of joint CFO and SFO estimation have been averaged over 1000 Monte Carlo simulation. The number of epochs to train the NN is varied to evaluate the performance of the NN based joint CFO and SFO estimator. The SNR of the received signal is varied from 0 to 20 dB , number of transmit antenna $N_T = [1,2]$ and number of received antenna $N_R = [1,2,3,4]$ are considered for simulating the MIMO OFDM-OQAM system. CFO values are randomly chosen in between the interval $[-Fs/4 \;\; Fs/4]$ and SFO values are randomly chosen in between the interval $[-4/Ts \;\; 4/Ts]$.

Fig. 4 depicts MSE vs. SNR plots for the proposed NN based joint CFO and SFO estimation with filter bank compensation for MIMO OFDM-OQAM systems. Fig. 4 clearly shows that MSE reaches a very low value of 10^{-4} even at a very poor $SNR = 0\ dB$ having $N_T = 2$ and $N_R = 4$. This figure also shows that the estimation error reduces with increase in number of epochs.

Fig. 5 shows the probability of success of the classification performances of the proposed joint CFO and SFO estimator in slow fading and multipath channel in MIMO OFDM-OQAM systems. From Fig. 5, we can draw similar conclusion that the probability of success of the proposed estimation technique enhances with the increase of SNR and with the increase in the number of epochs required to train NN estimator. The proposed NN based joint CFO and SFO estimation technique could achieved 95% probability of success even at a very low $SNR = 0\ dB$.

Fig. 6 illustrates the BER vs. SNR performance for in the presence of the CFO and SFO with and without compensation using filter bank unit. This figure clearly depicts that the NN based estimation and filter bank compensation technique greatly improves the BER performance in the presence of CFO and SFO imperfections and it reaches the performance of MIMO OFDM-OQAM system without the presence of CFO and SFO imperfections.

5 Conclusion

An NN based joint estimation along with filter bank compensation has been developed and evaluated for MIMO OFDM-OQAM systems. Performance evaluation through MATLAB simulation has been carried out to show the efficacy of the proposed technique to estimate and compensate the CFO and SFO imperfections even at a very poor $SNR = 0\ dB$ and with $N_T = 2$ and $N_R = 4$. Further, probability of success curve indicates the superiority of NN based classifier which shows the applicability of machine learning technique for future wireless communication.

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