KNN, k-Means and Fuzzy c-Means for 16-QAM Demodulation in Coherent Optical Systems

Alejandro Escobar Pérez, Jhon J. Granada Torres
Facultad de Ingeniera. GITA Research Group. Cl. 67 No. 53 108
Universidad de Antioquia
Medellin, Colombia
alejandro.escobarp@udea.edu.co, jhon.granada@udea.edu.co

***Abstract*—In this paper, Machine Learning (ML) techniques such as k-Nearest Neighbors (KNN), k-Means and Fuzzy c-Means (FCM) are implemented in coherent optical system with DSP-based receiver. Nyquist single carrier optical transmission at 32 Gbaud is simulated in VPIDesignSuite Software in co-simulation with Matlab. Simulations results shows gains up to 1 dB and 2 dB using ML techniques at 50 km of optical link with 100 kHz and 25 kHz of laser linewidth, respectively. Besides, it is demonstrated that ML techniques can be effectively used as a nonsymmetrical demodulation (NSD) method.**

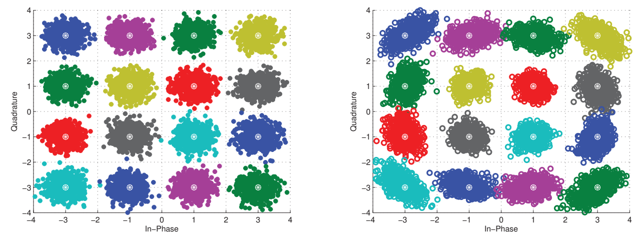
***Index Terms*—Machine Learning, 16-QAM, Coherent Optical Systems.**

I. Introduction

The growth of traffic in optical networks demands advanced and sophisticated digital signal processing (DSP) [1]. The use of linear and non-linear equalizers implemented in DSP-based coherent receivers has been the conventional method for mitigation of transmission system's impairments. However, high bit rates with different modulation formats, increases the computational complexity, forcing us to look for other techniques. Hence, Machine Learning (ML) techniques have been used in coherent optical systems, showing good performance with lower computational complexity [2].

Most of the ML techniques are applied to the In-Phase and Quadrature (IQ) signal components in post-slicing process [3]–[5] . It is due IQ components can be analyzed in a constellation diagram, for better comprehension of the received symbols' threshold. The IQ diagram shows the amplitude and phase value of every sampled data. In a 16-QAM format, the ideal constellation is drawn by white dots in Fig. 1a. Every drawn point correspond to a 4-bit symbol.

In any optical transmission, signals will be affected by electrical, optical and electro-optical devices and by channel impairments. It results in distortions in the received signal, seen as temporal variations in the I and Q components, generating non-desirable symbol position in the constellation diagram. For example, the presence of Additive White Gaussian Noise (AWGN), distorts the symbols position, creating a circular shape for every group of symbols [4] (see Fig. 1a). However, in high capacity optical links, several linear and nonlinear effects of the optical fiber and electrical/optical devices, such as phase noise [4], Bias drifting, IQ imbalance, high launch power, temperature and mechanical disturbances, among others, increases the symbol distortion resulting in non-gaussian shapes seen in the constellation diagram as it is shown in Fig. 1b [3]. Hence, Nonsymmetrical Demodulation (NSD) techniques are required to reduce symbol errors [4].



(a) 16-QAM constellation affected with Gaussian Noise. (b) 16-QAM constellation affected with Nonlinear Noise.

Fig. 1: 16-QAM constellations.

Our proposed NSD methods are based on two unsupervised and one supervised ML algorithms: k-Means, Fuzzy c-Means (FCM) and k-Nearest Neighbors (KNN), respectively. Additionally, Least Mean Squares (LMS) equalizer module is introduced before ML technique, for intersymbol interference mitigation, and carrier recovery. The optical communication system were modeled in VPIDesignSuite Software and the proposed ML algorithms were implemented in Matlab.

A brief explanation of the ML techniques, adapted for NSD, is presented in section II; details of the simulation setup are given in section III; results and discussion are exposed in section IV; finally, conclusion and future work is shown in section V.

II. Demodulation based on Machine Learning

KNN

K-Nearest Neighbors is a classification machine learning algorithm that identifies different classes of data [6], [7]. With a previous training stage, the algorithm classifies data measuring Euclidean distance of each received symbol to its k nearest neighbors, where k is the number of neighbors, those neighbors are already classified data (similar to training sequences in equalization process) and based on the class of such neighbors, most common class is assigned to the symbol under analysis. For 16-QAM scenario, each generated symbol have one I and Q component, these values are the *features* of the data used in the ML process. Hence, each group of symbols (0 to 15) for 16-QAM modulation format, are the *class*. We explored the use of training data by emulating the distorted symbols in Matlab, avoiding the exhaustive data acquisition for real implementations, understanding the use of VPIDesignSuite's modules as blackboxes as in real scenarios. This training stage consists of 21 different constellations with symbol length of 10^3 each one, affected by the nonlinear distortions like phase noise and rotations with slight random variations and with SNR values from 0 dB to 25 dB. An example of one of these constellations is shown in Fig. 1b. The distance is calculated according to the equation:

$$d(X_q, X_i) = \sqrt{(I(X_q) - I(X_i))^2 + (Q(X_q) - Q(X_i))^2} \tag{1}$$

Where X_q is the analyzed symbol and X_i is arbitrary training point. This distance will be calculated k times due to the k different training points. Besides, k is usually an odd number for a better decision making. In our case, $k = 9$ shown the best performance.

k-Means

K-means is a clustering classification algorithm with hard partitioning of data (Each symbol will be part of only one cluster) [8], that calculates centroids given a number of clusters (16 for 16-QAM case). The initials values of centroids are given as the 16-QAM ideal constellation points. Classification starts by choosing closest centroid for each received symbol. The k-means algorithm is generalized by the equation (2) where k is the number of clusters. Centroid's position is updated by the mean estimation of the classified data (3). Algorithm iterates until centroids do not change their position [9]. n Is the total number of symbols that belong to the j cluster.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| (x_i^{(j)} - c_j) \right\|^2 \tag{2}$$

$$c_j = (1/n) \sum_{i=1}^{n} x_i^{(j)} \tag{3}$$

Fuzzy c-Means

Fuzzy c-Means is the fuzzy version of k-Means algorithm [4]. It gives to each symbol a probability to be part of a cluster [7]. Hence, the algorithm estimates for every single received symbol a membership degree associated to every cluster. It results in a partition matrix, whose factors are numbers from 0 to 1 and every factor is calculated following the equation (4), where N is the number of clusters, K is total received symbols, μ is the vector for closest cluster's centroid and r is the normalization matrix. For classification, it is assigned to each symbol, the cluster with the highest probability of belonging.

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} \left\| (x_n - \mu_j) \right\|^2 \tag{4}$$

III. Simulation Setup

Single carrier 16-QAM Nyquist coherent optical system at 32 Gbaud is modeled in VPIDesignSuite (see Fig. 2). Pseudo Random Binary Sequence (PRBS) with length of 65536 bits is generated to be mapped in 16-QAM modulation format. Optical modulation is based on single drive Mach-Zehnder Modulator (SD-MZM) including a continuous wave laser with different linewidth: 1 kHz, 25 kHz and 100 kHz. Launch power of 0 dBm and 9 dBm is guaranteed by ideal amplifier at the output of the optical transmitter. Signals are transmitted trough single mode nonlinear dispersive fiber (SM-NDF) with distances up to 90 km. Optical noise is injected to yield and OSNR values from 0 to 25 dB. The optical coherent receiver includes a laser with the same configuration as the one used at the transmitter side. DSP module includes chromatic dispersion compensation, clock recovery and 5-taps LMS equalizer using a training sequence of only 300 symbols.

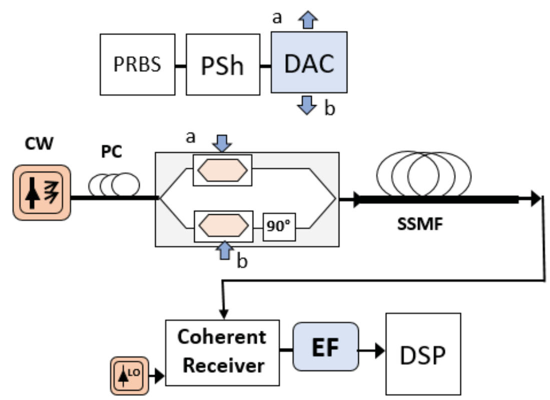


Fig. 2: Simulation setup.

IV. Results and Discussions

Our first step was the emulation of nonlinear noise-like distortions in Matlab. AWGN was added to yield OSNR values from 0 to 25 dB.

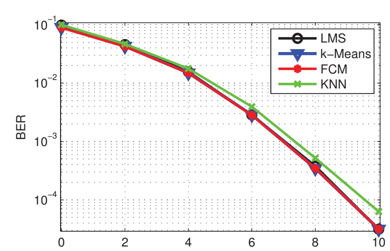
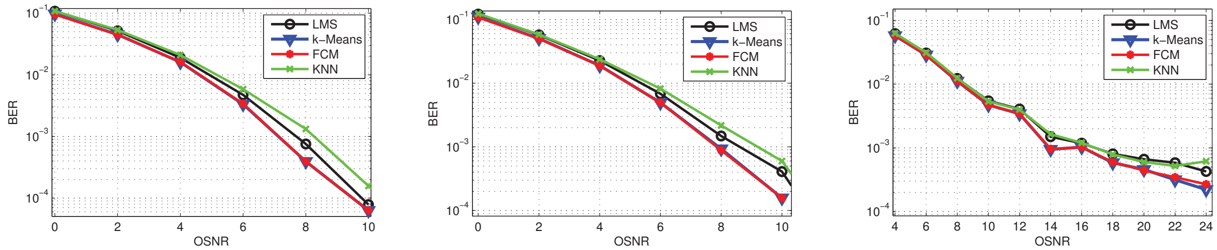


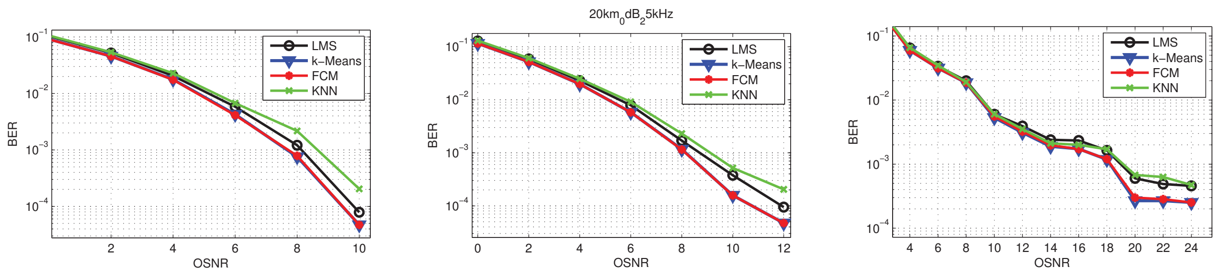
Fig. 3: OSNR vs BER for 16-QAM in Matlab.

Simulation of 16-QAM modulation format was introduced in such distortions emulation. LMS equalization was applied, and then, each ML technique were separately implemented

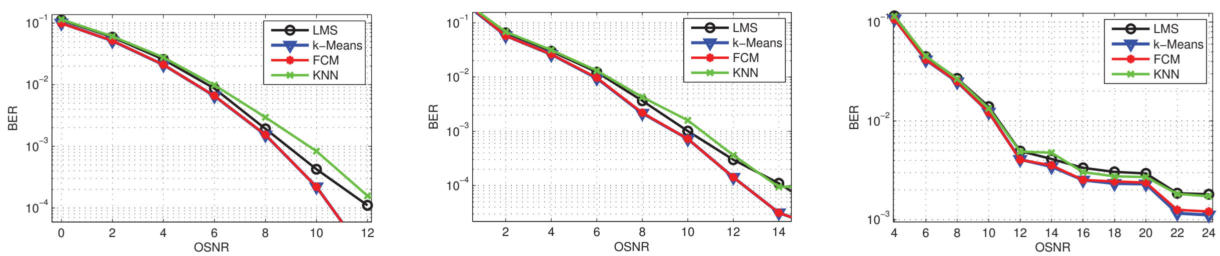


(a) Distance: 0 km, Linewidth: 1 kHz (b) Distance: 0 km, Linewidth: 25 kHz (c) Distance: 0 km, Linewidth: 100 kHz

Fig. 4: OSNR vs BER for 0 dBm launch power in B2B link.



(a) Distance: 20 km, Linewidth: 1 kHz (b) Distance: 20 km, Linewidth: 25 kHz (c) Distance: 20 km, Linewidth: 100 kHz



(d) Distance: 50 km, Linewidth: 1 kHz (e) Distance: 50 km, Linewidth: 25 kHz (f) Distance: 50 km, Linewidth: 100 kHz

Fig. 5: OSNR vs BER for 0 dBm launch power at 20 km and 50 km transmission distance.

after the equalizer module. BER vs ONSR curves are shown in Fig. 3. It is noticed that none of the three ML techniques improves the performance of LMS equalizer, this is because emulated effects in Matlab are totally mitigated by the LMS equalizer, leaving no errors to correct by the ML techniques.

Simulation of 16-QAM 32 Gbaud single-carrier coherent optical systems is performed on VPIDesingSuite Software, to evaluate the performance of such adapted ML techniques.

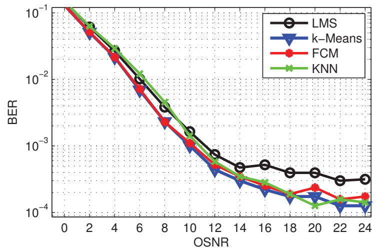
Fig. 4 shows BER performance vs OSNR for the coherent optical system, with launch power of 0 dBm, in back to back (B2B) scenario. Fig. 5 shows the cases of 25 km and 50 km of transmission distance using laser linewidth of 1 kHz, 25 kHz and 100 kHz.

In Fig. 4a, it can be seen a sightly gain of $\sim$ 0.2 dB by using both clustering techniques (k-Means and FCM). Due to it's B2B, the clustering corrects the impact of optical devices impairments, such as laser linewidth.

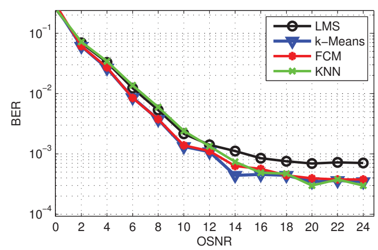
In Fig. 5e, a BER value of 1×10^{-4} is reached at 14 dB after LMS equalization, while this same BER was reached by using clustering at 12 dB, being the highest gain achieved for cases with launch power of 0 dBm. For 100 kHz linewidth scenarios, results using clustering techniques shown a BER value around 2×10^{-4} after 20 dB for 20 km (see Fig. 5c) and 1.3×10^{-3} after 22 dB for 50 km of transmission distance (see Fig. 5c). Clustering techniques outperforms the BER in comparison with only electrical equalization, for all the cases simulated with a launch power of 0 dBm. KNN did not show better performance than LMS equalization. Actually, the performance was worst in scenarios of 1 kHz and 25 kHz of laser linewidth.

Scenarios of 90 km transmission distance were simulated with laser linewidth of 25 kHz and 100 kHz, BER values of 1.7×10^{-3} and 1.9×10^{-2} were obtained by using clustering at 12 dB and 16 dB, respectively, keeping the gain of 2 dB compared with LMS.

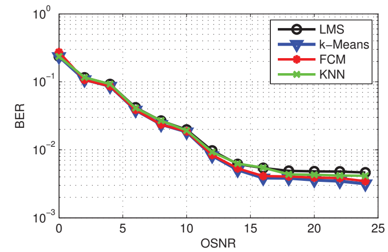
Fig. 6 shows BER vs OSNR curves for cases with launch power of 9 dBm for 20 km and 50 km of transmission distance. Gain of 2 dB using clustering is obtained for 20 km of transmission distance with 25 kHz of laser linewidth at 12 dB of OSNR (see Fig. 6b). After 14 dB of OSNR, the BER obtained by using the adapted ML techniques, is higher than 3.1×10^{-3}, 5×10^{-3}, 1.6×10^{-2} for 1 kHz, 25 kHz and



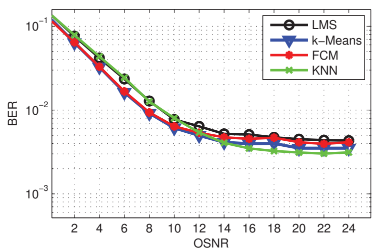
(a) Distance: 20 km, Linewidth: 1 kHz



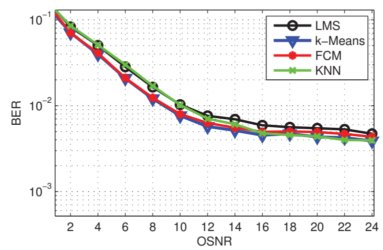
(b) Distance: 20 km, Linewidth: 25 kHz



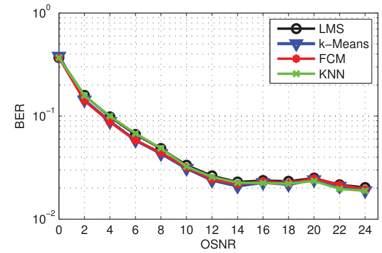
(c) Distance: 20 km, Linewidth: 100 kHz



(d) Distance: 50 km, Linewidth: 1 kHz



(e) Distance: 50 km, Linewidth: 25 kHz



(f) Distance: 50 km, Linewidth: 100 kHz

Fig. 6: OSNR vs BER for 9 dBm launch power at 20 km and 50 km transmission distance.

100 kHz, respectively, at 50 km of transmission distance. For launch power of 9 dBm, KNN's performance is always better than LMS's in terms of BER, except when 100 kHz linewidth is used at 50 km transmission distance (see Fig. 6f), obtaining BER values higher than 1.8×10^{-2}.

V. Conclusions

K-Nearest Neighbors, k-Means and Fuzzy c-Means algorithms were adapted for 16-QAM nonsymetrical demodulation in a coherent optical system. Algorithms were implemented in DSP-based coherent receiver, after LMS equalizer module. Results showed that KNN slightly increases the BER when launch power of 0 dBm. It is due to nonlinear effects of the optical fiber are not stimulated and the training data was chosen with symbols affected by nonlinear distortions. Whilst with launch power of 9 dBm, for 1 kHz and 25 kHz of laser linewidth, a gain up to 2 dB is obtained. The use of clustering techniques (k-Means and FCM), outperforms conventional demodulation in all cases, presenting both, same performance for all scenarios. As future work, authors will work in the modification of FCM, to reduce BER with stochastic assignation to cluster, modifying the rule of highest membership degree.

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