Affinity propagation clustering for blind nonlinearity compensation in coherent optical OFDM

E. Giacoumidis¹, I. Aldaya², J. L. Wei³, C. Sanchez⁴, H. Mrabet⁵, and L. P. Barry¹ 1: Dublin City University (DCU), The Rince Institute, Glasnevin 9, Dublin, Ireland. <u>elias.giacoumidis@dcu.ie</u>

2: School of Electrical and Computer Engineering, University of Campinas, Campinas, SP, Brazil.

3: Huawei Technologies Düsseldorf GmbH, European Research Center, Riesstrasse 25, 80992 München, Germany.

4: Aston Institute of Photonic Technologies (AIPT), Aston University, Birmingham, B4 7ET, UK.

5: Saudi Electronic University, College of computation and Informatics, IT Department, Saudi Arabia.

Abstract: The first blind nonlinear equalizer using affinity propagation (AP) clustering is experimentally demonstrated for single-channel and WDM CO-OFDM. AP outperforms fuzzy-logic c-means clustering and digital-back propagation for both QPSK and 16-QAM formats. **OCIS codes:** (060.2330) Fiber optics communications; (060.1660) Coherent communications; (060.4080) Modulation.

1. Introduction

Endeavors to surpass the Kerr nonlinearity limit in long-haul coherent communications have been attempted in digital domain by Volterra-based nonlinear equalization (V-NLE) [1] and digital-back propagation (DBP) [2]. V-NLE and DBP however, can only tackle deterministic nonlinearities such as self-phase modulation, without considering the stochastic nonlinear interaction from polarization-mode dispersion and amplified spontaneous emission noise caused by cascaded optical amplifiers. On the other hand, full-step DBP (FS-DBP) is very complex and V-NLE shows marginal performance enhancement accompanied with a significant amount of floating-point operations, thus forbidding their implementation in real-time communications. Moreover, albeit the Kerr-induced nonlinear process is deterministic, in multicarrier schemes like coherent optical OFDM (CO-OFDM) the resulting nonlinear interaction between subcarriers becomes very complicated appearing random due to its high peak-to-average power ratio (PAPR) [3]. Recently, unsupervised and supervised machine learning such as K-means clustering [4] and artificial neural network classification [3] have been introduced in optical communications to combat stochastic source of noises, performing blind and non-blind NLE, respectively. Here, we demonstrate the first blind-NLE using affinity propagation (AP) clustering for single-channel and WDM CO-OFDM. AP outperforms fuzzy-logic C-means (FL) and K-means clustering, as well as digital deterministic solutions such as FS-DBP and V-NLE, by reducing a significant amount of stochastic nonlinear noise on middle subcarriers.

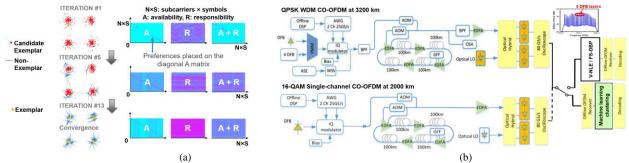


Fig. 1. (a) Affinity propagation (AP) clustering procedure (e.g. QPSK). (b) Experimental setup for single- and multi-channel CO-OFDM.

2. Affinity propagation (AP) clustering performance in CO-OFDM

In clustering, defined data learn a set of centers such that the sum of squared errors between data points and their nearest centers is small [5]. When the centers are selected from actual data points, they are called "exemplars." K-means begins with an initial set of randomly selected exemplars and iteratively refines this set so as to decrease the sum of squared errors [4]. In AP [5], every symbol is a potential exemplar and by viewing each symbol as a node that recursively transmits real-valued messages (separately for amplitude and phase) along the edges of the NLE network until a good set of exemplars and corresponding clusters emerges. 'Messages' are updated by simple formulas that search for minima of an appropriately chosen energy function. At any symbol in time the magnitude of each message reflects the current affinity that 1 symbol has for choosing another symbol as its exemplar. Let x_1 through x_n be a set of complex data (symbol), with no assumptions made about their internal structure, and let *S* be a function that quantifies the similarity between any 2 symbols, such that $S(x_i, x_j) > S(x_i, x_k)$ if x_i is more similar to x_j than to x_k . For this example, the negative squared distance of 2 symbols was used i.e. for points x_i and x_k , $s(i,k) = -||x_i - x_k||^2$. The diagonal of *S* (i.e. *S*(i,i)) is particularly important, as it represents the input preference,

meaning how likely a particular input is to become an exemplar. When this is set to the same value for all inputs, it controls how many classes the algorithm can produce. A value close to the minimum possible similarity produces fewer classes, however, a value close or larger to the maximum possible similarity, produces many classes (initialized to the median similarity of all pairs of inputs). AP proceeds by alternating 2 message passing steps to update the '*responsibility*, R(i, k)' and '*availability*, A(i, k)'matrices, where R quantifies how "well-suited" x_k is to serve as the exemplar for x_i compared to other candidate exemplars, while A shows how "appropriate" it would be for x_i to pick x_k as its exemplar, taking into account other points' preference. R and A, are initialized to zero being viewed as log-probability tables and then AP is iteratively updated for R and A by:

$$R(i,k) = s(i,k) - \max_{k' \neq k} \{a(i,k') + s(i,k')\} (1) , \quad A(i,k) = \min(0, r(k,k) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq \{i,k\}} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq k} \max(0, r(i',k))_{\text{for } i \neq k} (2) + \sum_{i' \neq i' \neq$$

The exemplars are extracted from the final updated matrices where 'responsibility + availability' is positive. Fig. 1(a) shows the aforementioned AP iterative result of R and A for QPSK middle-channel in WDM CO-OFDM at 3200 km for optimum launched optical power (LOP) per channel of -5 dBm, where 13 iterations are required for convergence. While K-means and AP are deterministic types of clustering, probabilistic also exist such as FL [6], permitting the symbols to fluctuate the data membership degree. The experimental setup shown in Fig. 1(b) for both single-channel and WDM CO-OFDM at 2000 km and 3200 km of transmission, respectively, are identical to Refs. [7,8]. 400 OFDM symbols (20.48 ns length) were generated using a 512-point IFFT on 210 QPSK/16-QAM subcarriers. To eliminate inter-symbol-interference from linear effects, a cyclic prefix (CP) of 2% was included. For clustering, FS-DBP, V-NLE and without (w/o) NLE, the raw bit-rates were ~20 Gb/s (QPSK) and 40 Gb/s (16-QAM). The offline OFDM demodulator included timing synchronization, frequency offset compensation, channel estimation and equalization with the help of an initial training sequence, as well as IQ imbalance and dispersion compensation using an overlapped frequency domain equalizer. For WDM CO-OFDM a laser grid of 100 kHz-linewidth DFBs on 100 GHz grid was used. The NLEs performances were assessed by Q-factor (= $20log_{10}[\sqrt{2}erfc^{-1}(2BER)]$)) measurements averaging over 10 recorded traces (~ 10^6 bits) by error counting (HDD).

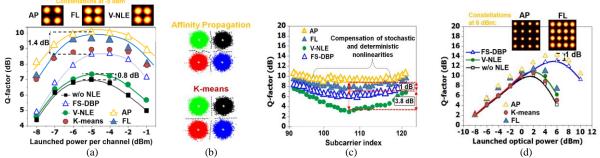


Fig. 2. (a) Q-factor vs. launched optical power (LOP) per channel for QPSK. (b) Received constellation diagrams at -7 dBm of LOP. (c) Middle subcarriers Q-factor distribution at -5 dBm of LOP. (d) Q-factor vs. LOP for single-channel 16-QAM CO-OFDM.

In Fig. 2(a), the Q-factor against the LOP per channel is plotted for all adopted NLEs for QPSK (middle channel) WDM CO-OFDM and in Fig. 2(b) constellations are depicted for AP and K-means at -7 dBm of LOP. AP tackles nonlinearities more effective than FL [6], K-means, FS-DBP and V-NLE since it compensates parametric noise amplification and the accumulated inter-subcarrier four-wave mixing (FWM) which appears random (due to high PAPR). This is corroborated in Fig. 2 (c), where the Q-factor for the middle subcarriers is plotted which suffers the most mainly from FWM (secondary from cross-phase modulation). In Fig. 3(c), we show that AP is effective for single-channel 16-QAM at high LOPs enhancing the Q-factor by 1 dB over FS-DBP, while significantly outperforming the benchmark clustering algorithms and V-NLE.

3. Conclusion

We experimentally demonstrated the first AP clustering-based blind NLE in single-channel and WDM CO-OFDM for up to 3200 km of transmission. AP outperformed FL, K-means, FS-DBP and V-NLE for both QPSK and 16-QAM formats, by reducing a significant amount of stochastic nonlinear noise on middle subcarriers.

Acknowledgements: EU Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 713567, SFI CONNECT Research Centre and Sterlite Techn. Ltd. We thank S. T. Le (Nokia/Bell labs) and M. E. McCarthy (Oclaro) for their contribution.

4. References

- [1] E. Giacoumidis et al, IEEE Phot. Techn. Lett. 26, 1383-1386 (2014).
- [3] M. A. Jarajreh et al, IEEE Phot. Techn. Lett. 27, 387-390 (2015).
- [5] B. J. Frey and D. Dueck, Science. 315, 972-976 (2007).
- [7] E. Giacoumidis et al, OSA Opt. Lett. 40, 5113-5116 (2015).
- [2] G. Gao et al, in Proc. OFC, OSA, 2016, p. OM3A.5.
- [4] D. Wang et al, IEEE Phot. Techn. Lett. 28, 2102-2105 (2016).
- [6] T. Nguyen et al, IEEE Trans. on Fuzzy Syst. 24, 273-287 (2016).
- [8] E. Giacoumidis et al, in Proc. OFC, OSA, 2017, p. Th2A.62.