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Optimized Decision Method Based on K-means-TKNN for Coherent Optical Communication Systems

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Introduction

To satisfy the rapidly increasing capacity demands, utilizing high-order QAM formats in coherent optical communication systems is a feasible solution. However, the performance of high-order QAM systems is seriously impacted by nonlinearity. K-Nearest Neighbors (KNN), as a classical machine learning algorithm, is an effective method to mitigate the nonlinearity, due to the flexibility and adaptive capacity.

In this paper, a K-means-Tailored KNN (TKNN) algorithm is proposed for nonlinear equalization in high-order QAM systems. By multi-level processing of test data, tailoring training data, and introducing the weighted-voting rule, K-means-TKNN algorithm can effectively mitigate nonlinearity while greatly reducing the computational complexity compared with the traditional KNN algorithm.

Principle

For M-QAM coherent optical transmission systems, the specific steps of the K-means-TKNN algorithm are shown in Fig.1.

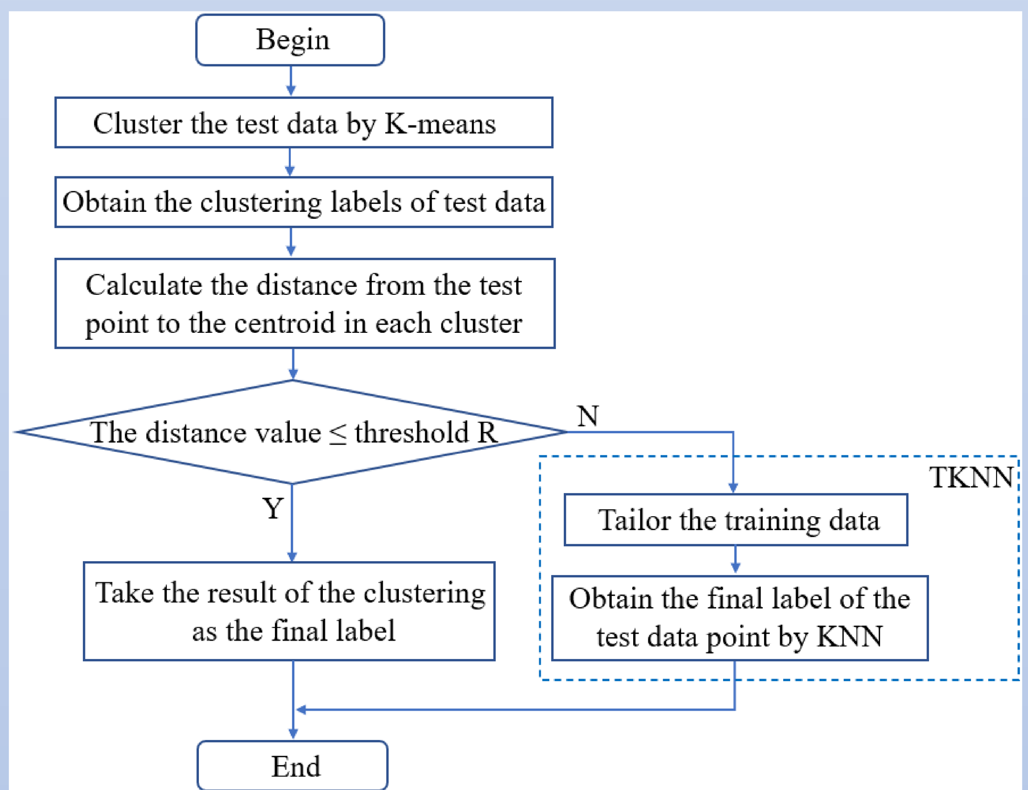


Fig 1. The flow chart of K-means-TKNN algorithm

a) All test data points from the receiver are clustered by K-means algorithm, and the clustering labels of test points and M centroids can be obtained after algorithm converging. b) The multi-level processing of test data. The Euclidean distance from the test point to the centroid is calculated in each cluster. If the distance is less than the threshold value R, the final label of the test point is equal to the clustering label in step a). Otherwise, the final label is obtained through TKNN described in the following step c). c) Tailoring the training data. The approximate position of the test data point is determined according to its label by k-means, and the training data close to the test point are used as the tailored training set. In addition, the weighted-voting rule is introduced to improve the classification accuracy.

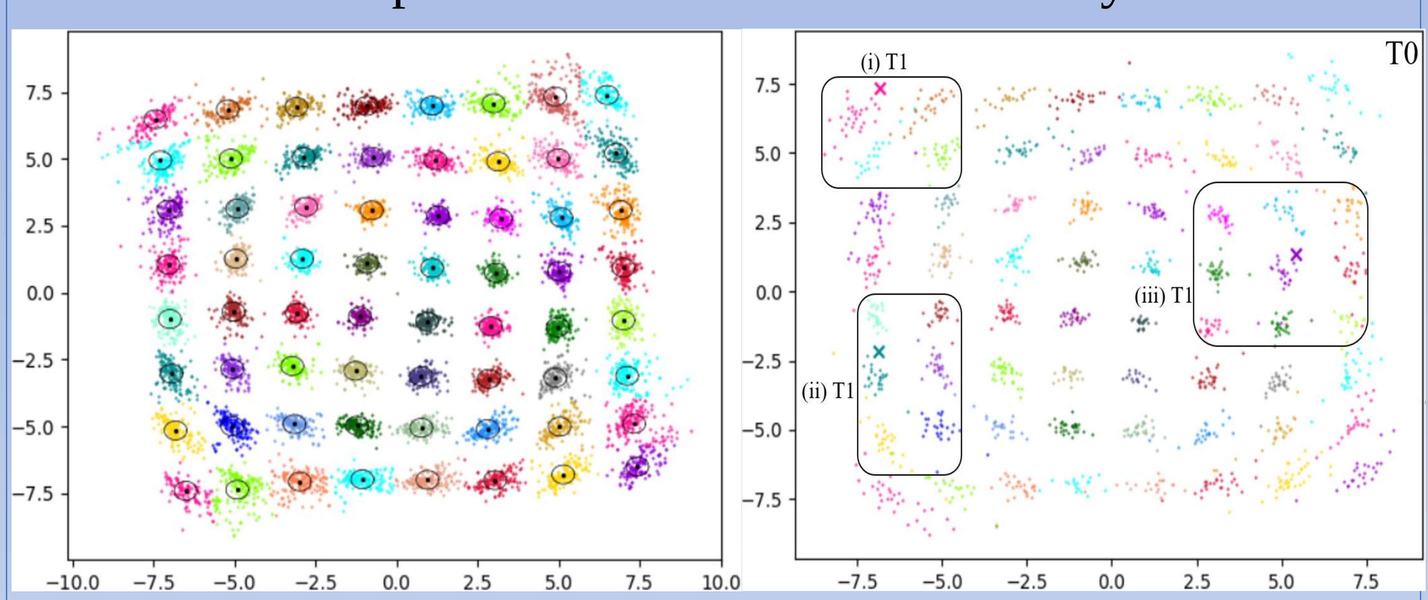


Fig 2. The application of K-means-TKNN in the 64-QAM system: (a) multi-level processing of test data; (b) tailor training data to obtain novel training set T1.

Simulation and results

The performance of K-means-TKNN is verified in a 300km 60-Gb/s single-carrier 64-QAM simulation system in Fig. 3. To make K-means-TKNN algorithm achieve better nonlinear equalization effect, it is necessary to optimize the parameters k, R and e. Fig. 4 shows that the BER curves of K-means-TKNN algorithm versus parameters k, R and e, when launched power into fiber (Pin) is 1dBm, 2dBm and 3dBm respectively. Through our analysis, in order to achieve better BER performance of system, the parameter values of k, R and e can be selected at around k=7, R=0.56 and e=21%, respectively.

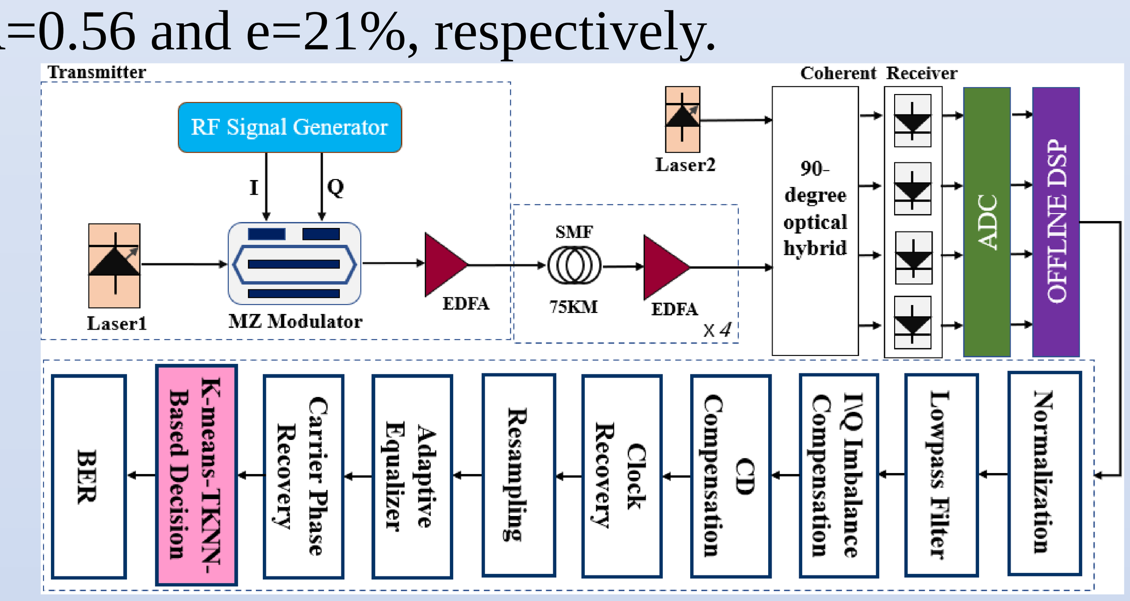
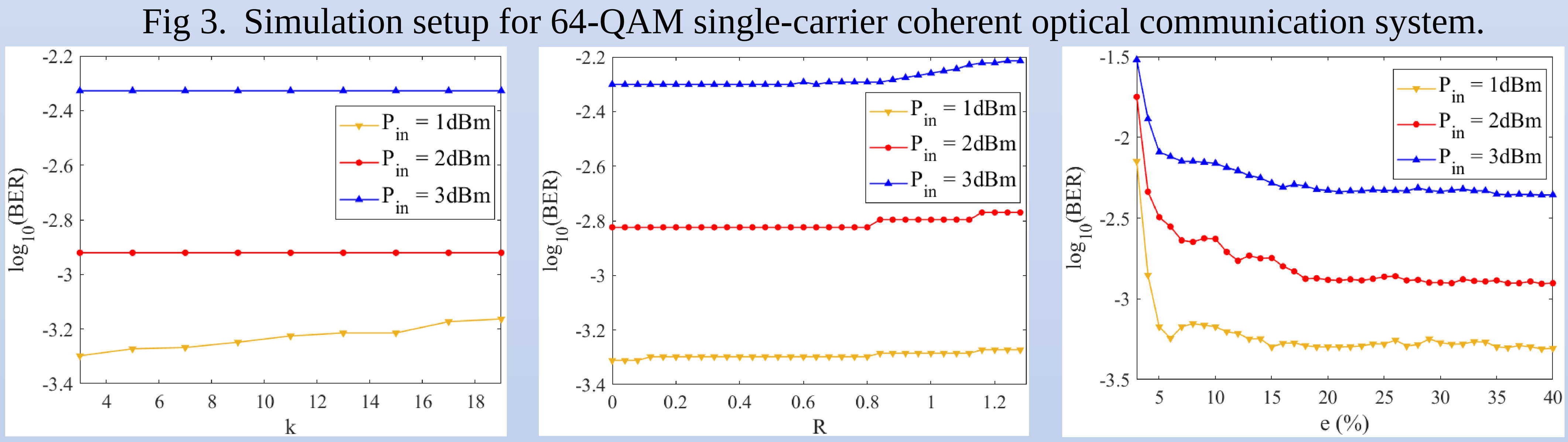


Fig 3. Simulation setup for 64-QAM single-carrier coherent optical communication system.



(a) (b) (c)

Fig 4. BER of K-means-TKNN versus parameters k, R and e respectively, when Pin is 1dBm, 2dBm and 3dBm: (a) k of the nearest neighbors; (b) threshold value R in multi-level processing of test data; (c) training overhead e.

BER is calculated by changing Pin from -5dBm to 4dBm as shown in Fig. 5. The results show the performance of K-means-TKNN is slightly better than that of traditional KNN. For a Hard-Decision (HD) Forward Error Correction (FEC) threshold of 3.8e-3, K-means-TKNN can obtain gains of 0.85dB, 0.60dB, and 0.07dB compared with MED decision, K-means and KNN respectively.

Table I shows the computational complexity of the above algorithms by calculating average running time. The running time of K-means-TKNN can be reduced to 20.3% of that of KNN.

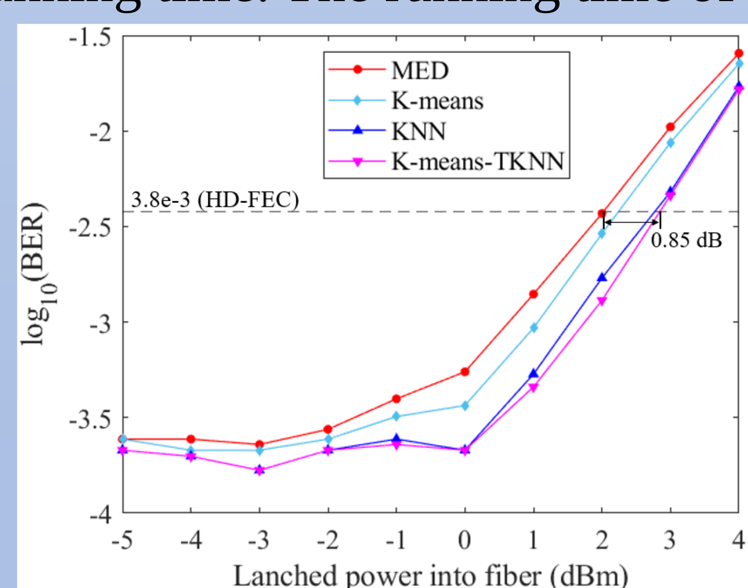


Fig 5. BER curves of the algorithms.

Table I. Running time of nonlinear mitigation methods

Nonlinear Mitigation Methods	Running Time (s)
KNN	131.32 (100%)
K-means-TKNN	26.73 (20.3%)
K-means	10.54 (10.54%)
MED decision	4.31 (3.3%)

Conclusion

A K-means-TKNN algorithm is proposed to mitigate nonlinearity for high-order QAM systems. In this method, K-means makes the first decision for all the test data, and TKNN makes the second decision for the partial test data suffering more noise. The performance of K-means-TKNN is verified in a 60-Gb/s single-carrier 64-QAM simulation system at 300km. The results indicate that K-means-TKNN can achieve slightly better nonlinear equalization effect than traditional KNN algorithm.

Acknowledgements

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