BIC-Based Optimization of the Identification of Multipath Propagation Clusters in MIMO Wireless Systems

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***Abstract*—A novel framework to optimize the identification clustering of multipath scatterers in a MIMO wireless system is proposed. It is a comprehensive evaluation of major cluster identification methods across multiple categories of clustering methodologies. The reliability will be ensured with the use of a parameter selection framework utilizing the Bayesian Information Criterion (BIC). Statistical preprocessing with support vector decomposition and normalization will also be handled.**

***Index Terms*—Radio propagation, multipath channels, channel models, clustering methods, clustering algorithms, optimization.**

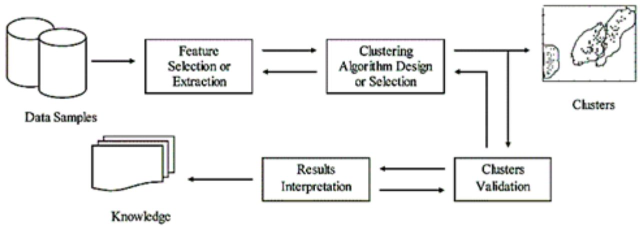

Fig. 1. Typical clustering procedure [9].

1. Introduction

Multiple-input multiple-output (MIMO) channel models are developed with the aid of accurate knowledge of the channel. Accurate descriptions of the propagation channel are important in the development of channel models [1], [2] . These models aim to improve the efficiency of MIMO communications system design [3], [4]. Studies have performed clustering on the multipath components generated in a MIMO wireless communication system [1], [5], [6]. The process of clustering here allows the extraction of valuable data relating to channel characteristics. A verified cluster of multipath components (MPCs) can signify the existence and approximate location of interacting objects (IOs) and scatterers, among other information.

Multiple authorities in the field of clustering offer various taxonomies of clustering algorithms [7]–[9]. Yet, most of these existing works agree that there is no "superior" algorithm for all occasions. A priori knowledge on the task to be handled is a key factor in the parametrization and subsequent performance of a certain clustering algorithm. But each one does have their own advantages and limits which give users guidelines for their use and application.

This work aims to provide a base framework or structure of optimization of clustering methods which would benefit the antennas and propagation community with the use and analysis of MPCs, its channel environment, and the subsequent channel modeling. This also optimizes methodologies in each of the major divisions of clustering techniques for the application and use for MIMO systems. It will be localizing current developments in the field of clustering and data analysis [10]–[12]. This improves on and is different from existing work [1], [5], [6] which mostly exclusively use one to two clustering methodologies, mostly involving K-means which although popular is attributed to weaknesses which are improved upon by other methods [7]–[9]. The introduction of BIC as a parametrization method will ensure the elimination of user bias while improving the clustering methods for the specified application.

2. Proposed Optimization Methodology

The implementation of other types of clustering algorithms, however, are limited in the field of multipath propagation. The current research gap in MPC clustering along with the opportunity for optimization and standardization in the exploration of other clustering techniques and methods are unique and novel. Following the typical clustering procedure at [9] (Fig. 1), the feature selection and extraction methodology will be adapted through the developed double-directional radio channel of [13]. This is in line with the COST 2100 channel model to be used to generate the reference multipath clusters and channel environment emulation for rigorous testing of the clustering algorithms [14], [15]. A plot of MPC clusters, the base station and mobile station locations, and visibility regions (VRs) generated from the COST 2100 Urban channel is shown in Fig. 2. The dimensions for obtaining the multipath component distance from such channel snapshot serves as the inputs to each considered clustering methodology.

The second key step in the clustering procedure involves the clustering algorithm selection. This study will encompass five key clustering algorithms representing different major clustering techniques to provide a detailed analysis of their respective performance. These are (1) K-means, (2) Fuzzy C-means, (3) Competitive Neural Networks, (4) Quantum Clustering, and (5) Support Vector Clustering.

The design and selection of the multipath cluster identification method will be handled through the localization

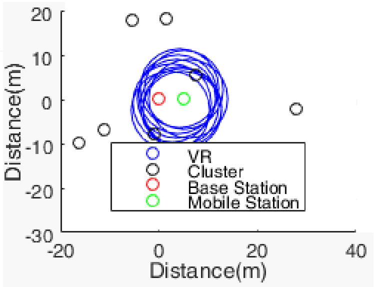

Fig. 2. Visualization of the visibility regions, clusters, and stations of the COST 2100 Urban Channel.

TABLE I
CLUSTERING OF COST 2100 URBAN CHANNEL MODEL

Clustering Method	η_{eff}	η_{jac}	η_{pur}
K-means	0.48958	0.25	0.33813
Fuzzy C-means	0.47917	0.2659	0.37398
Neural Network Clustering	0.9375	0.091931	0.092497
Quantum Clustering	0.79167	0.11095	0.11429
Support Vector Clustering	0.97917	0.054116	0.054179

and implementation of a parametrization framework. The use of the Bayesian Information Criterion (BIC) has been established to have a positive effect on algorithm performance [12]. This will allow for the elimination of designer bias in algorithm parametrization and standardized implementation of algorithm parameter optimization with respect to application and a priori information.

3. Results and Discussion

In order to evaluate the accuracy of the clustering methodologies, the Efficiency measure η_{eff}, Jaccard index η_{jac}, and Purity measure η_{pur} are used [16]. These metrics are defined as follows.

$$\eta_{\mathrm{eff}} = \frac{n_{11}}{n_{11} + n_{10}} \tag{1}$$

$$\eta_{\mathrm{jac}} = \frac{n_{11}}{n_{11} + n_{10} + n_{01}} \tag{2}$$

$$\eta_{\mathrm{pur}} = \frac{n_{11}}{n_{11} + n_{01}} \tag{3}$$

where n_{xy} is the number of pairs that are classified together, in the real classification if x is 1 and in the algorithm's classification if y is 1 and otherwise as such.

In Table I, Fuzzy C-means implementation has the best performance. All algorithms are more likely to have unmatched pair which are matched based on the real classification. The preliminary data show the varying performance of the algorithms in their unrefined state. These cannot act as benchmarks for comparison yet without the standardized framework for parameterization due to the inherent changes in performance parameterization can have on the clustering technique.

4. Conclusion

On the multipaths of an urban MIMO channel, the Fuzzy C-means algorithm performed best. K-means and Fuzzy C-means though are less versatile due to their requirement of having a fixed number of clusters. The performance of these algorithms were similar in their low purity score which also shows the most significant area of improvement. Future plans would involve the optimization of the data with the pre-processing and the optimization of the algorithms including three more to be implemented. This work can optimize MPC clustering for MIMO channels with a framework which will allow for greater flexibility for altering channel conditions. It will be limited in scope, however, to encompass the analysis of second-order clustering methods which incorporate combinations and modifications to the standard methodologies.

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References

[1] N. Czink, P. Cera, J. Salo, E. Bonek, J. P. Nuutinen, and J. Ylitalo, "Improving clustering performance using multipath component distance," *Electronics Lett.*, vol. 42, no. 1, pp. 33–5–, Jan. 2006.

[2] A. F. Molisch, "A generic model for MIMO wireless propagation channels in macro- and microcells," *IEEE Trans. Signal Process.*, vol. 52, pp. 61–71, Jan. 2004.

[3] P. Almers et al., "Survey of channel and radio propagation models for wireless MIMO systems," *EURASIP Journal on Wireless Communications and Networking*, vol. 2007, no. 1, pp. 1–19, 2007.

[4] H. Özcelik, "Indoor MIMO channel models," Ph.D. dissertation, Vienna University of Technology, Vienna, Austria, 2007.

[5] L. Materum, J. Takada, I. Ida, and Y. Oishi, "Mobile station spatio-temporal multipath clustering of an estimated wideband MIMO double-directional channel of a small urban 4.5 GHz macrocell," *Eurasip J. Wireless Commun. Netw.*, vol. 2009, no. 804021, pp. 1–16, Mar. 2009.

[6] N. Czink, P. Cera, J. Salo, E. Bonek, J. p. Nuutinen, and J. Ylitalo, "A framework for automatic clustering of parametric MIMO channel data including path powers," in *IEEE Veh. Technol. Conf.*, Sep. 2006, pp. 1–5.

[7] A. K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: A review," *ACM Comput. Surv.*, vol. 31, no. 3, pp. 264–323, Sep. 1999.

[8] B. S. Everitt, S. Landau, M. Leese, and D. Stahl, *Cluster Analysis*. Chichester: Wiley, 2011.

[9] R. Xu and D. Wunsch, "Survey of clustering algorithms," *IEEE Trans. Neural Netw.*, vol. 16, pp. 645–678, May 2005.

[10] M. Zhu, G. Eriksson, and F. Tufvesson, "The COST 2100 channel model: Parameterization and validation based on outdoor MIMO measurements at 300 MHz," *IEEE Trans. Wireless Commun.*, vol. 12, pp. 888–897, Feb. 2013.

[11] J. Poutanen, K. Haneda, L. Liu, C. Oestges, F. Tufvesson, and P. Vainikainen, "Parameterization of the COST 2100 MIMO channel model in indoor scenarios," in *Proc. 5th European Conf. Antennas Propagation*, Apr. 2011, pp. 3606–3610.

[12] R. Varshavsky, D. Horn, and M. Linial, "Clustering algorithms optimizer: A framework for large datasets," in *Proc. Bioinformatics Research Appl.*, 2007, pp. 85–96.

[13] M. Steinbauer, A. Molisch, and E. Bonek, "The double-directional radio channel," *IEEE Antennas Propag. Mag.*, vol. 43, no. 4, pp. 51–63, Aug. 2001.

[14] R. Verdone and A. Zanella, Eds., *Pervasive Mobile and Ambient Wireless Communications*. London: Springer-Verlag, 2012.

[15] L. Liu. A public COST 2100 channel model Matlab source code,. http://ftp.cost2100.org/WG2.3_Model/.

[16] R. Varshavsky, M. Linial, and D. Horn, "COMPACT: A comparative package for clustering assessment," in *Proc. Parallel Distributed Process. Appl.*, 2005, pp. 159–167.