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Performance of deep divergence and shallow learning approaches in clustering wireless multipaths

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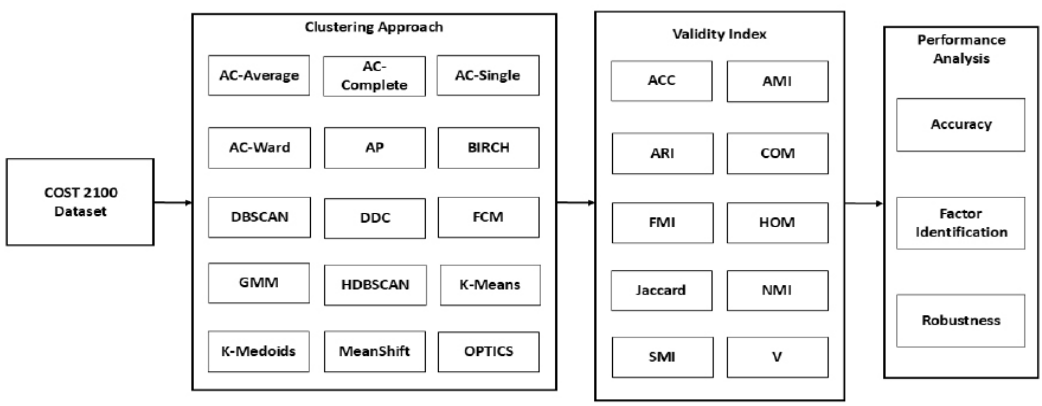
Graphical Abstract



Abstract

Channel modeling can be used to evaluate the performance of wireless communications systems. The European Cooperation in Science and Technology (COST) 2100 channel model (C2CM) can reproduce the multiple-input multiple-output (MIMO) channels' stochastic properties over time, frequency, and space. Multipath components with similar properties in delay and angles form multipath clusters. Multipaths have been clustered by shallow (non-deep learning) approaches over the years. The rise of deep learning approaches makes them good candidates in multipath clustering, but studies in this area remain rare. Thus, this study investigates the performance of Deep Divergence-Based Clustering (DDC) in grouping the multipaths from the COST 2100 dataset and measuring the performance with fourteen well-known shallow approaches. Ten different validation metrics evaluate the clustering results. DDC has the highest scores in ACC (0.3935), AMI (0.5346), and FMI (0.3102) in the semi-urban scenarios. Results indicate that the performance of DDC is close to the shallow clustering approaches. Thus, DDC can be used in clustering multipaths.

Keywords: channel model; clustering algorithm; MIMO

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Introduction

Fifth-generation (5G) wireless systems improve interconnecting devices' speed and bandwidth capability to meet the demands for new applications [1]. Since 5G wireless systems are expensive to build, it is crucial to evaluate their performance first [2]. Channel modeling evaluates the performance of wireless communications systems [3]. Various channel models [4–7] have been used over the years, and one of the latest is the C2CM [8]. COST 2100 replicates the stochastic properties of MIMO channels [9]. Groups of multipath components (MPCs) comprise a multipath cluster. The wireless channels are defined by multipath components and multipath clusters [10,11].

Clustering of multipaths has been done using different clustering approaches over the years [12–20]. With the advent of deep learning (DL), it has been used in image classification [21], object detection [22], segmentation [23], time series prediction [24], speech recognition [25], and clustering [26]. However, to the best of the authors' knowledge, DL applications to multipath clustering problems remain rare in the literature. Thus, Deep Divergence-Based Clustering (DDC), a DL clustering algorithm, is applied in this study to cluster the COST 2100 dataset, and its performance is compared for the first time with the results of shallow (non-DL) clustering approaches. DDC has the highest scores in ACC (0.3935), AMI (0.5346), and FMI (0.3102) in the semi-urban scenarios. It is the most robust when applied to larger datasets.

Background and Related Studies

The growth of wireless communications systems from fourth-generation (4G) to 5G [1] and the planning for the sixth-generation (6G) [27] wireless systems brought forth the development of new technologies. Technological advancement improved the capability and capacity of wireless communications systems, and the upgrade in the technology results in a more complicated wireless network. Building the communications backbone takes a lot of time and resources. Hence, the correct design is a must before its construction.

Wireless channel models. Channel models characterize the propagation channel of the communications system that is being designed. Among the popular channel models are Saleh-Valenzuela (SV) [4], 3rd Generation Partnership Project (3GPP) [5], Institute of Electrical and Electronics Engineers (IEEE) 802.15.4a [6], Wireless World Initiative New Radio (WINNER) II [7], and COST 2100 [8]. Cluster-based channel models are widely used in MIMO channel development. An accurate channel model is vital in the optimal performance of MIMO systems.

Multipath clustering approaches. In C2CM, signals from the transmitter to the receiver propagate in different directions. MPCs with similar parameters such as delay, azimuth of departure and arrival, and elevation of departure and arrival are grouped in clusters. A clustering approach groups the MPCs in different channel scenarios to determine the performance of the channel model [28].

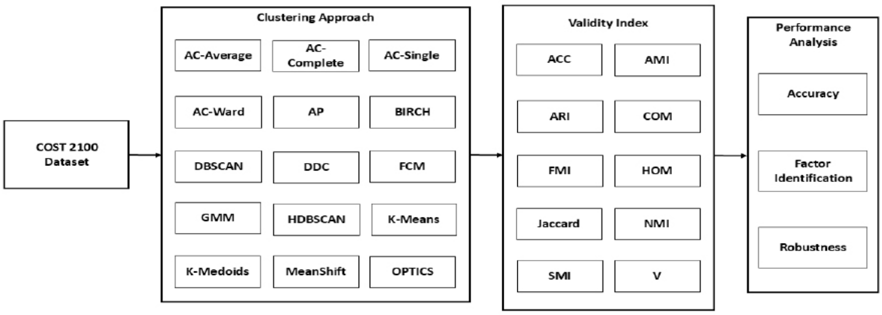

Figure 1. Conceptual diagram of the methodology.

Different clustering techniques have been used to cluster various datasets over the years. Among them are K-means [29], affinity propagation [30], mean shift [31], Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [32], Ordering Points to Identify the Clustering Structure (OPTICS) [33], and Balanced Iterative Reducing and

Clustering Using Hierarchies (BIRCH) [34]. These non-DL clustering techniques are classified as shallow approaches in this study.

For multipath clustering, KPowerMeans (KPM) [12], Kernel-Power Density (KPD) [14], and Gaussian Mixture Model (GMM) [19] have been used. However, they were not applied to the COST 2100 dataset.

Recently, DL has been used to cluster various datasets. DDC [26], in particular, is applied in clustering images, digits, and news stories. This study looks into the feasibility of DL in multipath clustering. Specifically, the work aims to use DDC in clustering multipaths from the COST 2100 dataset and compare its performance with shallow (non-DL) clustering approaches.

Materials and methods

Figure 1 outlines the overall methodology of the study. The COST 2100 dataset [36] is clustered using fifteen clustering approaches. The clustering results are validated using ten metrics, and the clustering performance is then analyzed.

The COST 2100 dataset. The dataset [37] consists of two indoor and six semi-urban channel scenarios. Band 1 Line-of-Sight Single Link and Band 2 Line-of-Sight Single Link for the indoor scenarios while Band 1 Line-of-Sight Single Link, Band 1 Line-of-Sight Multiple Links, Band 1 Non-Line-of-Sight Single Link, Band 2 Line-of-Sight Single Link, Band 2 Line-of-Sight Multiple Links, and Band 2 Non-Line-of-Sight Single Link for the semi-urban scenarios.

There are thirty sheets of data with a different number of multipath clusters and MPCs for each channel scenario. Each sheet of data has seven columns representing the parameters of each MPC. The parameters are the angle of departure's whitened x-component (X_AOD_W), whitened y-component (Y_AOD_W), and whitened z-component (Z_AOD_W), the angle of arrival's whitened x-component (X_AOA_W), whitened y-component (Y_AOD_W), and whitened z-component (Z_AOD_W), and the whitened delay (delay_W). The dataset serves as input to the clustering approaches and the ground truth for the validation metrics.

Clustering of the COST 2100 dataset. The following approaches cluster the dataset: Deep Divergence-Based Clustering (DDC), Agglomerative Clustering-Average (AC-Average), Agglomerative Clustering-Complete (AC-Complete), Agglomerative Clustering-Single (AC-Single), Agglomerative Clustering-Ward (AC-Ward), Affinity Propagation (AP), Balanced Iterative Reducing and Clustering Using Hierarchies (BIRCH), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Fuzzy C-Means (FCM), Gaussian Mixture Model (GMM), Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), K-Means, K-Medoids, MeanShift, and Ordering Points to Identify the Clustering Structure (OPTICS).

DDC is a DL clustering approach, while the rest are shallow (non-DL) approaches. Simulations are done in Python using the Scikit-Learn library.

Evaluation of results. The results of clustering are assessed using different performance metrics to show how the clustering approaches fared in grouping the COST 2100 dataset. The validation indices are as follows:

Accuracy (ACC) – predicted set labels must exactly match the corresponding ground truth set labels

Adjusted Mutual Information (AMI) – the measure of the similarity between two labels of the same data is adjusted to account for chance

Adjusted Rand Index (ARI) – the proportion of agreement with correction for chance relative to the total number of element pairs

Completeness Score (COM) – checks if all the data points that are members of a given class are elements of the same cluster

Fowlkes Mallows Index (FMI) – the proportion of positive agreements relative to the number of pairs belonging to the same cluster in one partition

Homogeneity Score (HOM) – checks if all of its clusters contain only data points that are members of a single class

Jaccard Score – the ratio of the intersection over the union of two label sets

Normalized Mutual Information (NMI) – normalization of the measure of the similarity between two labels of the same data to scale the results between 0 and 1

Spatial Mutual Information (SMI) – a fraction of labels that are incorrectly predicted is subtracted from one

V-Measure (V) – the harmonic mean between homogeneity and completeness and is identical to NMI

The score ranges from 0 to 1. A high value indicates a good similarity between the ground truth and the calculated data.

Table 1. Indoor scenarios performance metric means where highest mean in bold.

	ACC	AMI	ARI	COM	FMI	HOM	Jaccard	NMI	SMI	V
AC-Average	0.7661	0.7743	0.6651	0.9277	0.7188	0.8559	0.5809	0.8887	0.5353	0.8887
AC-Complete	0.7758	0.7824	0.6805	0.9277	0.7276	0.8660	0.5905	0.8947	0.5316	0.8947
AC-Single	0.7399	0.7494	0.6306	0.9223	0.6940	0.8348	0.5493	0.8735	0.5312	0.8735
AC-Ward	0.8256	0.8250	0.7492	0.9400	0.7863	0.8926	0.6782	0.9146	0.6370	0.9146
AP	0.5502	0.6078	0.3787	0.9604	0.5234	0.6419	0.3055	0.7493	0.2755	0.7493
BIRCH	0.7803	0.7890	0.6892	0.9300	0.7349	0.8702	0.5985	0.8981	0.5455	0.8981
DBSCAN	0.1748	0.1578	0.0489	0.9671	0.3011	0.1419	0.0972	0.2210	0.1293	0.2210
DDC	0.7226	0.7359	0.5789	0.9416	0.6517	0.8036	0.4675	0.8658	0.3760	0.8658
FCM	**0.8337**	0.8269	0.7521	0.9395	0.7810	**0.9029**	0.6615	**0.9205**	0.5882	**0.9205**
GMM	0.8300	0.8270	0.7511	0.9415	0.7871	0.8943	0.6775	0.9162	0.6213	0.9162
HDBSCAN	0.2029	0.2251	0.0943	0.9900	0.3400	0.2095	0.1230	0.2920	0.1427	0.2920
K-Means	0.8284	**0.8297**	**0.7533**	0.9424	**0.7887**	0.8962	**0.6801**	0.9178	**0.6379**	0.9178
K-Medoids	0.7401	0.7178	0.6128	0.8949	0.6588	0.8464	0.5011	0.8697	0.4438	0.8697
MeanShift	0.3428	0.3108	0.1220	0.9273	0.3415	0.3420	0.1407	0.4815	0.1769	0.4815
OPTICS	0.1172	0.0272	0.0066	**0.9922**	0.2702	0.0246	0.0765	0.0385	0.1118	0.0385

Table 2. Semi-urban scenarios performance metric means where highest mean in bold.

	ACC	AMI	ARI	COM	FMI	HOM	Jaccard	NMI	SMI	V
AC-Average	0.2260	0.2356	0.0957	0.5261	0.2391	0.2571	0.1122	0.3271	0.1068	0.3271
AC-Complete	0.2772	0.3473	0.1358	0.5236	0.2379	0.3700	0.1317	0.4296	0.1123	0.4296
AC-Single	0.1630	0.1209	0.0851	0.5332	0.2545	0.1554	0.1066	0.1936	0.1086	0.1936
AC-Ward	0.3692	0.5001	0.2374	0.6087	0.2954	0.5358	0.1892	0.5694	**0.1235**	0.5694
AP	0.3299	0.4995	0.2306	**0.6709**	0.2884	**0.6439**	0.1589	**0.6085**	0.0569	**0.6085**
BIRCH	0.3477	0.4740	0.2039	0.5992	0.2735	0.5069	0.1636	0.5486	0.1102	0.5486
DBSCAN	0.1927	0.1955	0.0297	0.5174	0.1773	0.1958	0.0557	0.2700	0.0665	0.2700
DDC	**0.3935**	**0.5346**	0.2583	0.6419	**0.3102**	0.5635	0.1851	0.5998	0.0898	0.5998
FCM	0.2291	0.3143	0.1620	0.4926	0.2719	0.2890	0.1487	0.3497	0.1143	0.3497
GMM	0.3793	0.4904	0.2388	0.5902	0.2882	0.5352	0.1875	0.5610	0.1138	0.5610
HDBSCAN	0.2314	0.2932	0.0337	0.6081	0.1832	0.3108	0.0580	0.3849	0.0510	0.3849
K-Means	0.3617	0.4894	0.2327	0.5986	0.2906	0.5269	0.1863	0.5600	0.1213	0.5600
K-Medoids	0.3804	0.5000	**0.2678**	0.5911	0.3042	0.5687	**0.1905**	0.5796	0.0988	0.5796
MeanShift	0.1190	0.0905	0.0160	0.4452	0.1963	0.1058	0.0500	0.1660	0.0579	0.1660
OPTICS	0.1533	0.1624	0.0094	0.6461	0.1926	0.1342	0.0469	0.2088	0.0566	0.2088

Performance analysis. The performance of the clustering approaches is analyzed based on accuracy, factor identification, and robustness. The validation indices give the accuracy of the clustering algorithms. The Analysis of Variance (ANOVA) assesses the validity indices, which serve as a statistical measure in comparing the significance of the results.

On the other hand, factor identification discovers why a particular clustering result is obtained. Lastly, robustness looks into the consistency of the clustering performance across all channels. A robust clustering approach performs consistently well in the eight-channel scenarios. The standard deviation of the validity indices evaluates the robustness of the clustering approaches.

Results and Discussion

The clustering results are evaluated using clustering accuracy, factor identification, and robustness.

Accuracy. The performance metric means for the indoor scenarios are shown in Table 1, while that of the semi-urban scenarios are presented in Table 2. The present work uses ten metrics for validating the clustering performance compared to just one or two in existing studies. K-Means has the highest score in five metrics in indoor scenarios. These are AMI (mean = 0.8297), ARI (0.7533), FMI (0.7887), Jaccard (0.6801), and SMI (0.6379). K-Means performs well when the dimension and the number of clusters are low. On the contrary, AP leads in four metrics in semi-urban scenarios. These are COM (mean = 0.6709), HOM (0.6439), NMI (0.6085), and V (0.6085). DDC has the highest score in the three metrics. These are ACC (mean = 0.3935), AMI (0.5346), and FMI (0.3102). DDC's good performance validates that DL approaches can be explored in clustering multipaths. The two clustering approaches tend to perform better when the number of multipaths and the number of clusters are increased. The COM metric has the best scores generated by the clustering approaches with a mean of 0.9430 for indoor scenarios and 0.5729 for semi-urban scenarios since it looks at the completeness of data in a cluster, while SMI is the least for all the channel scenarios with a mean of 0.4189 for indoor scenarios and 0.0926 for semi-urban scenarios due to high results that have incorrect data labels.

Factor identification. The clustering approaches performed better in indoor scenarios, as shown by the higher means in table 1 than in Table 2. This outcome is the consequence of having lower number of MPCs and multipath clusters in indoor scenarios. The number of MPCs ranges from 11 to 80 and the number of clusters from 4 to 27 in indoor scenarios. Moreover, the semi-urban scenarios have MPCs ranging from 458 to 1781 and more clusters from 14 to 66.

Robustness. The clustering approaches' box plots in indoor scenarios are shown in Figure 2. K-Means is the most robust since it registers the highest mean (red horizontal bar). The mean metric scores of the clustering approaches are significantly different since the p-value is 1.4229 x 10-22, which is less than the significant level of 0.05. These results show that the clustering approaches have different performances in clustering the multipaths.

Figure 3 presents the clustering approaches' box plots in semi-urban scenarios. DDC is the most robust since it has the highest mean (red horizontal bar). This result shows that DDC performs better than the other clustering approaches when applied to larger datasets. This outcome further points to the possibility of applying DL approaches in clustering multipaths. The p-value is 5.7569 x 10-5, indicating that the clustering approaches' mean metric scores are significantly different. This value validates the difference in the performance of the clustering approaches.

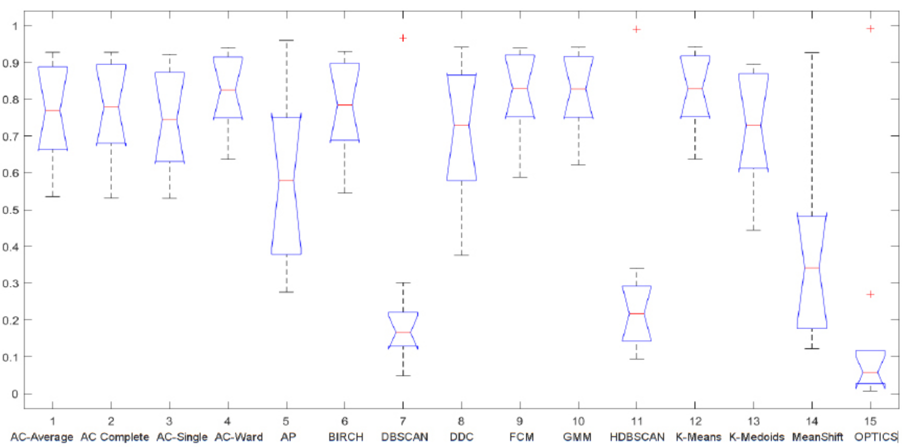

Figure 2. Box plots of the clustering approaches (horizontal axis) vs. the metric score (vertical axis) in indoor scenarios.

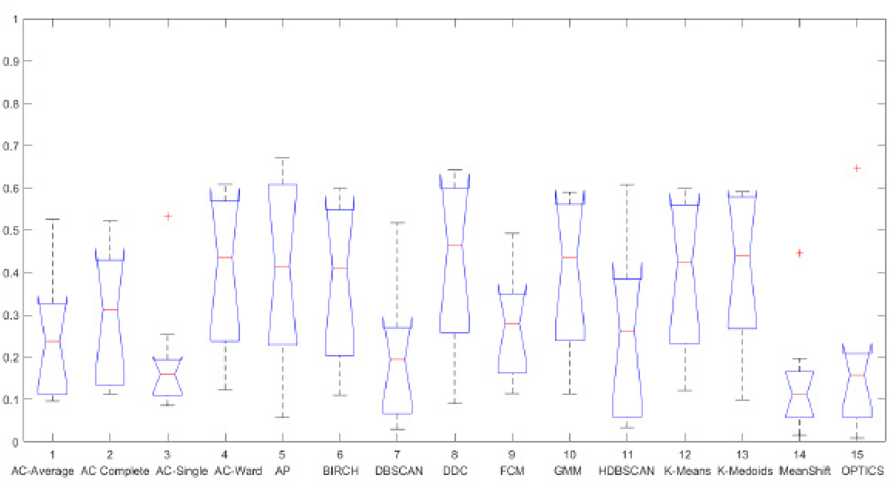

Figure 3. Box plots of the clustering approaches (horizontal axis) vs. the metric score (vertical axis) in semi-urban scenarios.

Conclusion

The work presents the performance of DDC and fourteen shallow approaches in clustering the COST 2100 dataset using ten validation metrics. Results show that DDC's performance is comparable with that of the shallow approaches. Furthermore, DDC has the best scores in ACC with a mean of 0.3935, AMI whose mean is 0.5346, and FMI with a mean of 0.3102 in the semi-urban scenarios. With the promising results manifested by DDC, DL approaches can be explored as alternatives in clustering multipaths.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, J.B. and L.M.; methodology, J.B. and L.M.; data collection M.C.; analysis and interpretation of data, J.B. and L.M.; original draft preparation, J.B.; review and editing of the draft, L.M. and M.C. All authors have read and agreed to the final version of the manuscript.

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Informed Consent Statement

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