

Joint DoA Estimation and AMC for Overlapped Signal via Multi-Task Deep Learning

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Abstract—In this paper, we propose a deep learning (DL)-based joint direction of arrival (DoA) estimation and automatic modulation classification algorithm to identify overlapped signals. The proposed algorithm utilizes independent component analysis for signal separation to estimate two characteristics of each signal within an overlapped signal. Each separate signal is processed by MoDANet, a multi-task deep learning model for joint characteristic estimation. The model estimates DoA and modulation type and maps these characteristics to the appropriate signal. The simulation results show that the proposed algorithm performs signal classification and estimation accurately.

Index Terms—Automatic modulation classification, direction of arrival estimation, overlapped signal, multi-task learning

I. INTRODUCTION

Direction of arrival (DoA) estimation and automatic modulation classification (AMC) are two important processes for detecting and recovering the overlapped unknown signal. DoA estimation utilizing data collected from an array of antennas determines the location of the signal sources [1]. AMC identifies the modulation type and recovers the signal without modulation-related information such as data rate and bandwidth allocation [2]. Thus, there have been a lot of efforts to estimate those two signal characteristics.

The conventional model-driven researches of DoA estimation and AMC degrade performance under channel uncertainties. [2]–[5]. In recent years, data-driven DL approaches have been studied to achieve higher estimation performance [6], [7]. The state-of-the-art DL-based approach, MoDANet [8], employs multi-task learning (MTL) [9] to perform DoA estimation and AMC simultaneously. MTL jointly learns multiple related tasks to improve their performance through shared knowledge across the tasks. MoDANet deals with single signals and is incompatible with overlapped signals. However, multiple unknown signals are received in practical wireless environments, so a simultaneous characteristics estimation for overlapped signals is required [10].

Independent component analysis (ICA) is considered one of the methods to separate blind overlapped signals [11]. ICA separates the overlapped signals by maximizing the statistical independence and non-Gaussianity of the individual signals. The main methods to maximize the independence are maximum-likelihood estimation [12], minimization of the mutual information between estimated signals [11], and neural network approach called infomax [13]. Through the above research, ICA has proven successful in separating overlapped signals.

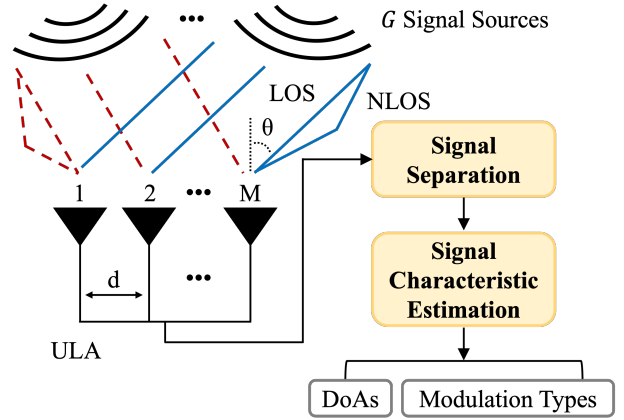


Fig. 1. Wireless signal reception and processing for joint DoA estimation and AMC.

In this paper, we propose an MTL-based joint DoA estimation and AMC algorithm for overlapped signals. The proposed algorithm separates overlapped signals into individual signals through independent component analysis (ICA), a widely used method for performing blind signal separation without prior information [11]. Then, MoDANet is applied to separate signals to estimate DoA and modulation types simultaneously. Through this progress, we can map the corresponding characteristics of the individual signals within the overlapped signals. The simulation results demonstrate that the proposed algorithm achieves accurate classification and estimation.

II. SYSTEM MODEL

The system model of the proposed algorithm shown in Fig. 1 includes both the signal separation stage and the characteristics classification stage at the receiving end. A uniform linear array (ULA) of M antenna elements with inter-element spacing d receives overlapped signals from G signal sources. Assuming the first antenna element as a referent phase point, the received signal vector from the far field $\mathbf{x}$ is expressed as

$$\mathbf{x} = \sum_{g=1}^G \mathbf{A}_g \cdot \mathbf{s}_g + \mathbf{n} \in \mathbb{C}^{M \times 1}, \quad (1)$$

where $\mathbf{A}_g \in \mathbb{C}^{M \times P}$ is the steering matrix of the g -th signal source, $\mathbf{s}_g \in \mathbb{C}^{P \times 1}$ is the multi-path modulated signal vector

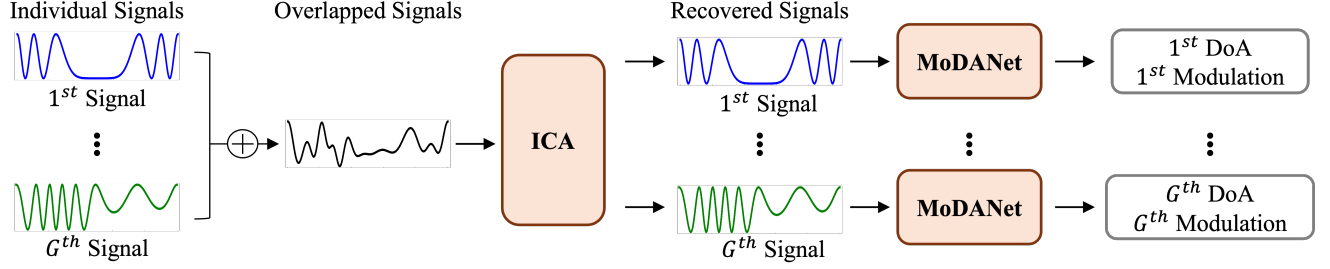


Fig. 2. The proposed joint DoA estimation and AMC algorithm for overlapped signals.

of the g -th signal source, and $\mathbf{n}$ is the additive noise. Each individual is statistically independent from all other signals and follows a non-Gaussian distribution. Considering both the line-of-sight (LOS) and non-line-of-sight (NLOS) components of the individual signals, $\mathbf{s}_g$ and $\mathbf{A}_g$ are expressed as

$$\mathbf{s}_g = [s_{g,0} \ s_{g,1} \ \cdots \ s_{g,(P-1)}]^\top, \quad (2)$$

$$\mathbf{A}_g = \begin{bmatrix} 1 & e^{-jv \sin \theta_{g,0}} & \cdots & e^{-jv(M-1) \sin \theta_{g,0}} \\ 1 & e^{-jv \sin \theta_{g,1}} & \cdots & e^{-jv(M-1) \sin \theta_{g,1}} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & e^{-jv \sin \theta_{g,(P-1)}} & \cdots & e^{-jv(M-1) \sin \theta_{g,(P-1)}} \end{bmatrix}^\top, \quad (3)$$

where P is the number of multi-path components and $s_{g,i} = \alpha_{g,i} s_g(t - \tau_{g,i})$ for $i = 0, \dots, P-1$. Here, $\alpha_{g,i}$ is the propagation attenuation coefficient, and $\tau_{g,i}$ is the time delay. $[\cdot]^\top$ denotes the transpose. Each element of $\mathbf{A}_g$ is determined by the angles of arrival $\theta_{g,i}$, where $\theta_{g,0}$ denotes the LOS component and the rest denote the NLOS components. $v = 2\pi d/\lambda$ represents inter-element phase shift, where λ denotes the signal wavelength. The analog output signals from the antenna array are sampled at T_s intervals for digitization. The digital signal $\mathbf{X} \in \mathbb{R}^{N \times M}$ with N complex samples is expressed as

$$\mathbf{X} = \begin{bmatrix} X_1(0) & X_1(T_s) & \cdots & X_1((N-1)T_s) \\ X_2(0) & X_2(T_s) & \cdots & X_2((N-1)T_s) \\ \vdots & \vdots & \ddots & \vdots \\ X_M(0) & X_M(T_s) & \cdots & X_M((N-1)T_s) \end{bmatrix}^\top. \quad (4)$$

III. JOINT AMC AND DOA ESTIMATION FOR OVERLAPPED SIGNAL

A. Signal Separation

The proposed two-step algorithm depicted in Fig. 2 comprises signal separation and characteristic estimation. The algorithm handles overlapped signals consisting of individual signals with different modulation types and DoAs. We leverage ICA to separate overlapped into sub-signals, assuming the mutual statistical independence of non-Gaussian individual signals. The ICA model is expressed as

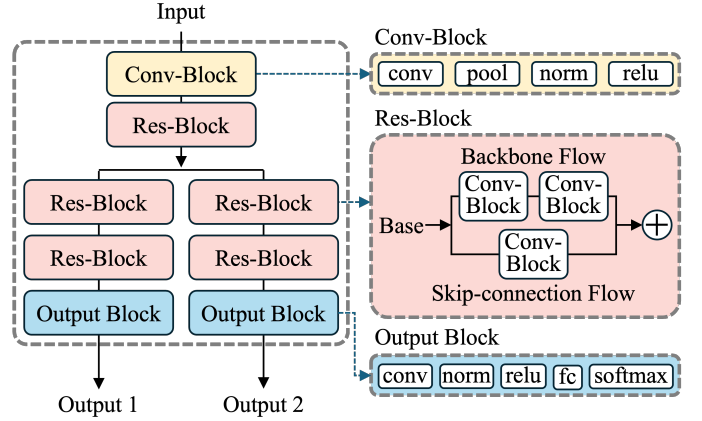


Fig. 3. MoDANet architecture [8].

$$\mathbf{Y} = \mathbf{W}\mathbf{X}^\top \in \mathbb{R}^{G \times N}, \quad (5)$$

where $\mathbf{Y}$ is the recovered source signal matrix without phase shift information from the antennas and $\mathbf{W} \in \mathbb{R}^{G \times M}$ is the estimated steering matrix. The ICA algorithm iteratively learns and updates $\mathbf{W}$ to ensure the statistical independence of sub-signals within the overlapped signal, thereby estimating the individual signals.

The recovered signal $\mathbf{Z}$ with phase shift information is obtained by multiplying the transpose of each row of $\mathbf{Y}$ with the corresponding row of $\mathbf{W}$.

B. Signal Characteristics Estimation

MoDANet is an MTL-based deep neural network for simultaneous DoA estimation and modulation classification. As depicted in Fig. 3, the MoDANet architecture comprises convolutional (conv)-block, residual (res)-block, and output block. The conv-block utilizes a conv layer to extract signal features from the input signal and emphasize meaningful features through max pooling (pool) and ReLU layers. The res-block consists of a backbone flow composed of two conv-blocks and a skip-connection flow composed of one conv-block. By adding skip-connection flow, the res-block reuses previously extracted features to enhance feature learning performance and

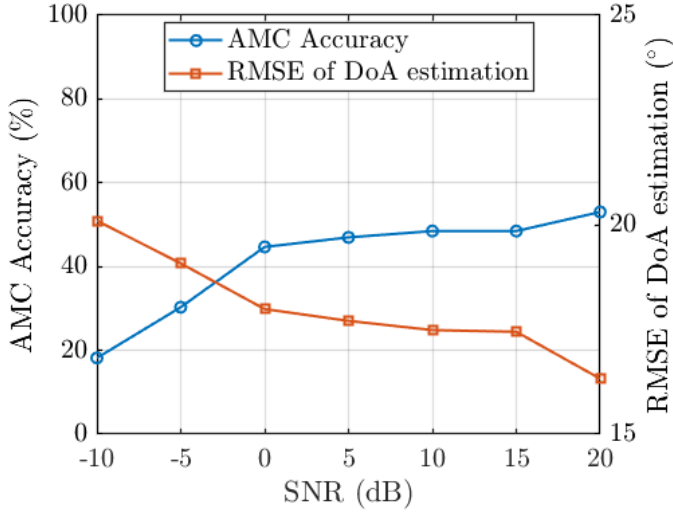


Fig. 4. AMC accuracy and DoA estimation RMSE of the proposed algorithm.

prevent vanishing problem. The output blocks utilize fully connected (fc) layers to map signal features with specific classes and softmax layers to derive classification results. Each of the two output blocks respectively determines the final results for AMC and DoA estimation.

The goal of the proposed algorithm is to estimate and map two characteristics of the separate signals simultaneously. To achieve this objective, we employ MoDANet to process each signal separated by ICA. ICA does not preserve the order or scale of signals during separation, making it difficult to identify the correspondence between separated and overlapped signals. As a result, determining true labels for the test dataset becomes a problem for performance evaluation.

To resolve the problem, we utilize the DoAs and modulation types of overlapped signals as the true labels of the test dataset. We utilize the trained MoDANet with individual signals before overlapping. For evaluation, the model tests the separate signals by ICA from overlapped signals. The true labels for the separate signals are set to the DoAs and modulation types of the overlapped signals.

IV. SIMULATION RESULTS AND DISCUSSIONS

A. Dataset Generation and Training Process

The training dataset [8] comprises 450, 120 signals, 12 different modulation types (including PSK, QPSK, 8PSK, QFSK, 8FSK, 16APSK, 16QAM, 64QAM, 4PAM, LFM, DSB-SC, and SSB-SC), and 61 DoAs (discrete angles in the range $[0, 60]^\circ$ with the step size of 1°). From this dataset, we adopt a subset including all modulation types, 13 DoAs (in the range $[0, 60]^\circ$ with the step size of 5°), and 7 SNR levels (the Gaussian noise in range $[-10, 20]$ dB with step size of 5 dB) for the test. We leveraged the model trained in [8] with the training dataset. By section II, the overlapped signal is

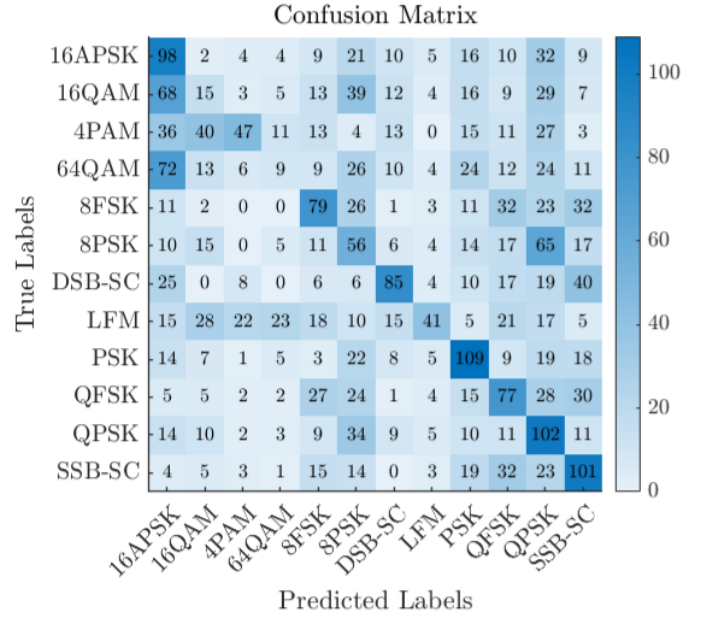


Fig. 5. Confusion matrix of AMC result when SNR is 20 dB.

generated from two individual signals in the test dataset. Each individual signal has a different modulation type and DoA.

B. Simulation Results

The performance of proposed algorithm including DoA estimation RMSE and AMC accuracy of the separate signals across SNR levels is presented in Fig. 4. For performance evaluation, accuracy means the percentage of correct classification and RMSE is defined as

$$\text{RMSE} = \sqrt{\frac{1}{J} \sum_{j=1}^J (\hat{\theta}_j - \theta_j)^2} \quad (6)$$

where J is the number of test signals, $\hat{\theta}_j$ is j -th predicted DoA, and θ_j is j -th true DoA.

As shown in Fig. 4, we analyze the RMSE of DoA estimation and AMC accuracy across SNRs. Simulation results demonstrate that the signal separation by ICA is more effective for modulation estimation of individual signals than DoA. At SNR 20 dB, the RMSE of DoA estimation is approximately 16° , while the AMC accuracy reaches about 55%. This discrepancy is attributed to the inadequacy of the steering vector estimated through the ICA.

Furthermore, the analysis highlights that while ICA effectively separates mixed signals, its performance is highly sensitive to noise levels, as reflected in the steep improvement in AMC accuracy and reduction in DoA RMSE with increasing SNR. The results underline the importance of developing complementary preprocessing techniques or adaptive models to enhance steering vector estimation accuracy, particularly in low SNR environments, for improved DoA performance.

The confusion matrix in Fig. 5 depicts the AMC accuracy of separate signals for all modulation labels at an SNR of 20 dB. Each cell represents the number of matches between true and predicted labels, visually illustrating prediction accuracy through colors. The diagonal elements of the matrix represent the number of correctly classified samples for each modulation type, indicating the model's ability to distinguish between modulation classes. For example, the classification results show that 16APSK and DSB-SC achieved 98 and 85 correct predictions, respectively, demonstrating the robustness of the model for these modulation types. These results underscore the strengths of the proposed algorithm in accurately classifying certain modulation types while revealing areas where further optimization is needed. In particular, reducing misclassifications among similar modulation types could be achieved by incorporating more advanced feature extraction techniques or by improving the discrimination capability of the classifier.

V. CONCLUSION

In this paper, we proposed a DL-based classification algorithm for estimating modulation types and DoAs in overlapped signals. The proposed utilizes ICA for overlapped signal separation and applies a MoDANet-based DL algorithm to estimate the two characteristics of each individual signal. Sentence to be inserted for simulation results. Through the results, we confirmed that the integration of ICA and MoDANet enables the estimation of multiple information parameters from overlapped signals, suggesting its applicability in practical communication scenarios with multiple signal sources. Future research will propose a DL architecture designed to outperform the MoDANet-based algorithm in estimation performance while achieving a balance between computational complexity.

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REFERENCES

- [1] Y.-S. Yoon, L. Kaplan, and J. McClellan, "Tops: new doa estimator for wideband signals," *IEEE Trans. Signal Process.*, vol. 54, no. 6, pp. 1977–1989, 2006.
- [2] R. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE Trans. Antennas Propag.*, vol. 34, no. 3, pp. 276–280, 1986.
- [3] A. Paulraj, R. Roy, and T. Kailath, "A subspace rotation approach to signal parameter estimation," *Proc. IEEE*, vol. 74, no. 7, pp. 1044–1046, 1986.
- [4] J. L. Xu, W. Su, and M. Zhou, "Likelihood-ratio approaches to automatic modulation classification," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 41, no. 4, pp. 455–469, 2011.
- [5] S. Huang, Y. Yao, Z. Wei, Z. Feng, and P. Zhang, "Automatic modulation classification of overlapped sources using multiple cumulants," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 6089–6101, 2017.
- [6] H. Huang, J. Yang, H. Huang, Y. Song, and G. Gui, "Deep learning for super-resolution channel estimation and doa estimation based massive mimo system," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8549–8560, 2018.
- [7] F. Meng, P. Chen, L. Wu, and X. Wang, "Automatic modulation classification: A deep learning enabled approach," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10 760–10 772, 2018.

- [8] V.-S. Doan, T. Huynh-The, V.-P. Hoang, and D.-T. Nguyen, "Modanet: Multi-task deep network for joint automatic modulation classification and direction of arrival estimation," *IEEE Commun. Lett.*, vol. 26, no. 2, pp. 335–339, 2022.
- [9] R. Caruana, "Multitask learning," *Mach. Learn.*, vol. 28, pp. 41–75, 1997.
- [10] J. C. Clement, N. Indira, P. Vijayakumar, and R. Nandakumar, "Deep learning based modulation classification for 5G and beyond wireless systems," *Peer-to-Peer Netw. Appl.*, vol. 14, no. 1, pp. 319–332, 2021.
- [11] P. Comon, "Independent component analysis, a new concept?" *Signal Process.*, vol. 36, no. 3, pp. 287–314, 1994.
- [12] D. T. Pham and P. Garat, "Blind separation of mixture of independent sources through a quasi-maximum likelihood approach," *IEEE Trans. Signal Process.*, vol. 45, no. 7, pp. 1712–1725, 1997.
- [13] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural comput.*, vol. 7, no. 6, pp. 1129–1159, 1995.