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OPEN CALL ARTICLE

Knowledge Transfer for Specific Emitter Identification: Fundamentals, Applications, and Meta-Learning Perspectives

Zherui Zhang, Shuang Li, Yinqiu Liu, Bin Ge, Qiling Gao, Yun Lin, *Senior Member, IEEE*, and Giorgio Taricco, *Fellow, IEEE*

Abstract

Radio-Frequency Fingerprinting (RFF)-based Specific Emitter Identification (SEI) enables device-level recognition by exploiting hardware-induced signal characteristics. However, practical wireless channels often mix RFFs with channel responses, receiver effects, and environmental interference, leading to cross-domain performance degradation. Existing transfer approaches such as parameter-efficient fine-tuning and distribution alignment can partially mitigate this gap, but they do not explicitly preserve the relational structure among emitter fingerprints, often resulting in overfitting or negative transfer under few-shot conditions. This article reviews knowledge transfer for wireless intelligence, covering its fundamental concepts, representative methods, and key applications. We further present a Meta-Learning-Guided Knowledge Transfer Network (MLGKFN) for SEI, which represents RFF-related relations through graph structures and learns transferable meta-knowledge for rapid adaptation to new environments. Specifically, MLGKFN encodes each 1,024-point IQ signal into eight signal-dependent node embeddings, dynamically constructs sparse RFF relations using attention with Top-k ($k = 3$) sparsification, and enables rapid few-shot adaptation across channel conditions through episodic meta-training. By combining relational knowledge transfer with meta-learning, this framework provides a promising direction for building wireless intelligence systems with stronger generalization and sample efficiency.

I. Introduction

Specific Emitter Identification (SEI) is a key technique for wireless security and spectrum intelligence because it recognizes individual transmitters through Radio Frequency Fingerprints (RFFs) caused by hardware imperfections [1]. Unlike protocol identifiers such as addresses or device IDs, RFFs are physically rooted in transmitter circuits and are therefore difficult to forge directly. This property makes SEI attractive for applications such as unauthorized device detection, spectrum monitoring, maritime surveillance, and secure access control. Deep learning based physical-layer signal recognition has further demonstrated the feasibility of extracting discriminative signal representations directly from received wireless signals [2]. As illustrated in Fig. 1, conventional transfer learning may mix RFF features with channel-dependent characteristics, leading to performance degradation under channel changes. In contrast, the meta-knowledge-guided approach learns transferable relational patterns through episodic training, enabling adaptation to new environments.

The main obstacle to practical SEI is that RFFs are observed through time-varying wireless channels. Large-scale real-world radio signal recognition studies have further shown that deep learning models may achieve promising performance on collected wireless signals, but their recognition reliability can degrade when the data distribution changes across practical environments [3]. A model trained in one environment may unintentionally learn channel-dependent shortcuts rather than device-intrinsic fingerprints. When the same transmitter is observed under a different propagation condition, receiver setting, or noise level, the learned representation can become unreliable. Therefore, the central challenge is not only to improve recognition accuracy in a fixed dataset, but also to transfer RFF-relevant knowledge across changing environments.

Knowledge transfer provides a natural solution to this challenge. By reusing information learned from source domains, transfer learning can reduce the amount of labeled target-domain data required for model adaptation. Existing approaches include transferring model parameters, aligning feature distributions, reweighting source samples, and preserving relational structures among samples or classes [4]. These methods have been widely explored in wireless signal processing tasks, but they still face difficulties in few-shot SEI, where only a small number of target

Zherui Zhang, Bin Ge, Qiling Gao (corresponding author), and Yun Lin are with Harbin Engineering University, Harbin 150000, China; Shuang Li is with the Inspur Electronic Information Industry Company Ltd., Jinan 250101, China; Yinqiu Liu is with the College of Computing and Data Science, Nanyang Technological University, Singapore 639798; Giorgio Taricco is with the Department of Electrical and Telecommunications Engineering, Politecnico di Torino, 10129 Torino, Italy.

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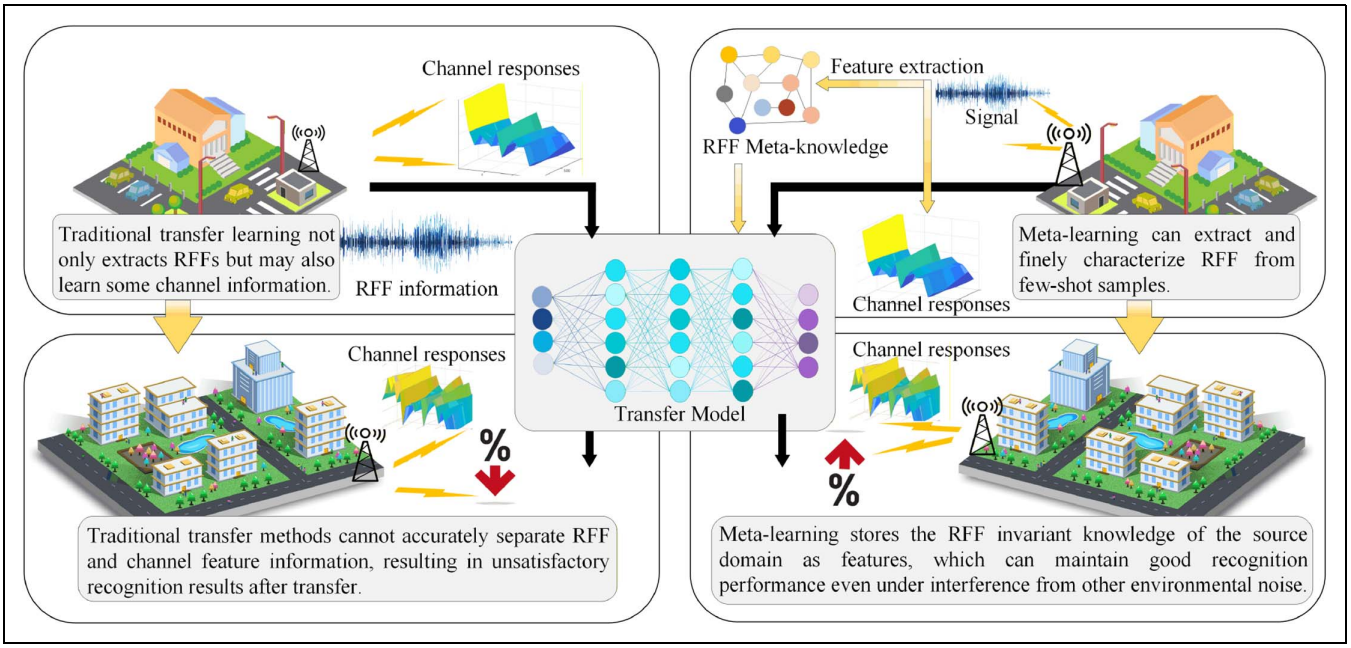


FIG. 1. A comparison between conventional transfer learning and meta-knowledge-guided knowledge transfer for SEI. Traditional transfer learning methods, when acquiring Radio Frequency Fingerprints (RFF), may inadvertently learn channel-dependent features, thereby leading to degraded recognition performance. The method proposed in this paper employs a meta-knowledge-guided mechanism that focuses on learning invariant features to enhance the model's robustness across different channels.

samples are available and the source-target gap may be severe.

Meta-learning offers a complementary perspective. Instead of only transferring a trained representation, meta-learning aims to learn how to adapt [5]. By constructing source-domain episodes that mimic future few-shot target-domain tasks, a meta-learning model can acquire an adaptation prior that helps it rapidly calibrate to new channels with limited labeled samples. This property is particularly suitable for SEI, where the model must distinguish stable hardware fingerprints from unstable channel effects.

Accordingly, this article is organized around a unified question: how can SEI remain reliable when the propagation environment changes but only a few labeled target-domain samples are available? We first review knowledge transfer mechanisms to identify what information can remain transferable across environments. This analysis motivates the combination of relational transfer, which preserves RFF-related relationships, and meta-learning, which learns how these relationships should be adapted. Based on this connection, we present Meta-Learning-Guided Knowledge Transfer Network (MLGKFN) as a concrete realization of this idea and finally use an AIS cross-day case study to examine its practical effectiveness. The main contributions of this article are summarized as follows:

- We review the foundations and major methodological categories of knowledge transfer, with a focus on their relevance to wireless signal intelligence.
- We discuss representative SEI and wireless-related application scenarios to illustrate how knowledge transfer supports robust adaptation under channel and environment shifts.
- We propose MLGKFN for SEI, which uses graph structures to model stable RFF relations and meta-knowledge to update them with only a few target-domain samples, enabling robust device identification under channel variations and supporting higher-layer wireless functions such as device authentication and spectrum access management.

The remainder of this article is organized as follows. Section II reviews the basic concepts and methodological categories of knowledge transfer. Section III discusses application scenarios in wireless communication. Section IV presents MLGKFN. Section V introduces the experiments. Section VI concludes the article.

II. Foundations of Knowledge Transfer for Wireless Communication

Traditional supervised learning is typically based on the assumption that training and test data are identically distributed. However, this assumption rarely holds true in real-world applications. For example, in wireless communication, data distribution can vary significantly across line-of-sight and non-line-of-sight channels, between static and mobile platforms, and even under different receiver settings such as sampling rate, carrier frequency, and noise conditions. These factors often lead to significant domain shifts and degrade the performance of models trained in fixed environments. Therefore, knowledge transfer holds immense potential in the communications field, especially when dealing with SEI.

A. Representative Methods in Knowledge Transfer

Knowledge transfer typically has two main objectives. First, it improves data efficiency in the target environment, especially when the number of labeled samples is small. Second, it enhances the cross-domain robustness of the model, enabling it to maintain stable performance even when the distributions in the target and source domains differ. These two objectives often coexist in signal and time series applications because the data in these applications is not only

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No.	Method	Description	Framework	Task	Key Contribution
1	Parameter Transfer	Pre-train on unlabeled data, then transfer parameters to incremental SEI [6].	Three-stage framework: pre-training task + pretext task + downstream task	SEI with few-shot samples and increment	This work integrates self-supervised learning into incremental SEI and designs a three-stage framework consisting of pre-training, pretext learning, and downstream recognition. Contrastive learning is used in the pretext task to exploit unlabeled samples.
2		Pre-train a robust extractor, then transfer its parameters for recognition [9].	Contrastive pretraining + Siamese classification + inference	SEI across channels and receivers	This work proposes a three-stage RFFI framework with contrastive-learning-enhanced pretraining, Siamese classification, and inference. It uses spectrogram representations to reduce the coupling between transmitter impairments, channel effects, and receiver impairments.
3	Feature Transfer	Transfer general representations to few-shot SEI [10].	Handcrafted features + few-shot learning	Few-shot SEI on WiFi and ADS-B	This work proposes a knowledge, data, and model-driven fusion framework for few-shot SEI. It combines handcrafted features, self-supervised learning, few-shot learning, and a hybrid neural network architecture.
4		Transfer cloud-learned features to edge recognition [11].	Cloud deep learning (DL) models + broad learning (BL) model	Edge-assisted SEI	This work proposes a deep cloud and broad edge framework for semi-supervised SEI. Cloud-side deep learning models and an updatable edge-side broad learning model jointly identify unlabeled RF signals, while new real-time signals are used to update the edge model.
5	Distribution alignment and reweighting	Align old and new domains via replay, distillation, and weighting [7].	Adaptive Domain-Incremental Learning with Knowledge Replay and Domain Alignment (ADIRA)	Domain-incremental SEI	This work proposes ADIRA, an adaptive domain-incremental SEI framework using knowledge replay, distillation, adaptive coefficients, and adversarial domain alignment. It combines embedding distillation loss with supervised contrastive loss to improve domain adaptation.
6		Use adaptive weighting under distribution mismatch [12].	Pairwise similarity + adaptive cross-entropy + entropy regularization	Open-world SEI	This work formulates a semi-supervised open-world SEI problem and proposes an end-to-end similarity-adaptive framework. It identifies novel classes through pairwise feature similarity, uses adaptive cross-entropy to balance known and novel classes, and applies entropy regularization to reduce overfitting.
7	Relational Transfer	Transfer class-prototype relations for incremental SEI [13].	Prototype learning + self-supervised contrastive learning (SSCL) + separation of class weights (SCW) + course learning	Few-shot class-incremental SEI	This work proposes FSCIL-SEI for few-shot class-incremental SEI. It uses prototype learning and self-supervised contrastive learning to improve feature separability, introduces separation of class weights to reduce forgetting, and adopts three-stage course learning to alleviate overfitting.
8		Use evolving prototypes to reduce forgetting and overfitting [8].	Open-Set Few-Shot Class Incremental Learning (OFSCIL) framework	Open-set few-shot class-incremental for SEI	This work proposes OFSCIL for few-shot incremental open-set recognition in SEI. It decouples the feature extractor from the classifier, introduces an evolving prototype classifier with prototype calibration, and designs a prototype-distance-based open-set classifier with semi-supervised clustering.

TABLE I. Overview of representative knowledge transfer methods for SEI.

scarce but also heterogeneous in several ways. For clarity, we organize existing approaches according to the dominant form of transferred knowledge into four non-exclusive views: parameter transfer, feature transfer, distribution alignment and reweighting, and relational transfer. These categories are analytical rather than mutually exclusive. In practice, a method may combine several mechanisms, such as parameter reuse together with feature alignment or relational constraints.

1) Parameter transfer: Parameter transfer is one of the most commonly used strategies in knowledge transfer. It first initializes the target domain model with parameters learned from the source domain task, and then fine-tunes the model. In the field of communications, changes in the source and target domains generally refer to channel variations and ambient noise fluctuations. This strategy is favored due to its simplicity and computational efficiency. However, its effectiveness largely depends on the similarity between the source and target domains. When channel or environmental noise changes too drastically, parameter transfer may lead to overfitting or unstable adaptation, and its performance is usually very sensitive to the choice of hyperparameters [6].

2) Feature transfer: Feature transfer methods aim to learn domain-invariant representations, making samples from the source and target domains more

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similar in the latent feature space. However, when domain differences are caused by variations in the underlying data generation mechanism, without prior knowledge of communication, the network struggles to distinguish between RFF and channel features during feature extraction. Moreover, excessive feature alignment may force different domains to share an overly compact representation, weakening class separability and suppressing task-relevant emitter features. As a result, the learned feature space may become insufficiently discriminative for downstream recognition, ultimately causing performance degradation or even negative transfer under severe cross-domain conditions. This observation suggests that feature transfer for wireless identification should not only pursue invariance, but also explicitly preserve hardware-related discriminative structure while suppressing shortcut channel features [1].

3) Distribution alignment and reweighting: Another important class of methods focuses on distribution alignment and sample reweighting. If the differences between the source and target domain data can be quantified, they can be reweighted based on the correlation between the source samples and the target domain, or a finer alignment can be performed in the latent space. The effectiveness of these methods largely depends on the type of distribution offset being dealt with, such as covariate offset, label offset, or variations in conditional distributions. However, for communication signals, many parameters, such as channel response or carrier offset, are difficult to estimate accurately [7].

4) Relational transfer: In many practical tasks, transferable knowledge is not only embedded in individual samples themselves, but also reflected in the structural relationships among samples, such as similarity patterns, graph topologies, category prototypes, and temporal dependencies. Relational transfer aims to explicitly model and preserve this structural knowledge, and then transfer it across different tasks or domains to enhance learning effectiveness. Compared with methods that focus only on feature distributions or parameter initialization, relational transfer pays more attention to the interaction patterns among samples, which often remain relatively stable even when the data distribution changes. Representative techniques in this category include graph neural networks, prototypical learning, and metric learning, all of which are designed to capture sample-to-sample or class-to-class relationships in an interpretable and transferable manner. This type of transfer is particularly valuable in low-sample or few-shot scenarios, where limited observations make it difficult for models to learn robust decision boundaries from individual samples alone. By introducing relational constraints, the model can better exploit the intrinsic structure of the data, improve feature discrimination, and achieve stronger generalization ability under cross-domain or cross-environment conditions [8].

B. The Role of Meta-Learning in Knowledge Transfer

Meta-learning can be viewed as a higher-level adaptation paradigm that complements the four transfer categories above. Rather than transferring a fixed set of features or weights, it transfers the adaptation strategy itself. Examples include an initialization that can be calibrated with a few gradient steps, a metric space that remains consistent across domains, and an update rule that improves adaptation reliability. By jointly optimizing for rapid adaptation and cross-domain generalization in a single episodic training objective, meta-learning bridges the gap between transfer learning and few-shot learning, making it especially attractive for wireless scenarios where labeled target data are limited and channel-induced distribution shifts are severe.

III. Applications of Knowledge Transfer in SEI and Wireless Communication

The value of knowledge transfer is particularly evident in wireless systems where labeled data are expensive and deployment environments change frequently must be made under uncertainty. Instead of training each model from scratch for every new scenario, knowledge transfer enables previously learned representations, domain-invariant structures, and relational knowledge to be reused across tasks, devices and environments. This capability is especially important for applications involving illegal emitter detection, spectrum scheduling, signal source identification, and autonomous driving, where the target domain often contains limited labels, unseen classes, or severe distribution shifts. Fig. 2 summarizes four knowledge transfer paradigms and their representative wireless applications. Parameter, feature, distribution, and relational transfer address different forms of cross-domain adaptation, supporting tasks such as illegal UAV detection, SEI, spectrum scheduling, and autonomous driving.

A. Detection of Illegal Uncrewed Aerial Vehicle Equipment

The rise of the low-altitude economy has made unauthorized drone activity a pressing safety issue, yet labels for illegal devices are inherently scarce. Knowledge transfer addresses this asymmetry by first learning stable hardware "fingerprint representations" from registered devices, and then deploying these representations for open-world monitoring, where unseen emitters are flagged as anomalies. This pipeline directly counters identity spoofing and model switching attacks without requiring labeled illegal-drone data.

B. Wireless Network Spectrum Scheduling

Spectrum scheduling must operate across regions, time-of-day, and devices with very different propagation statistics. Knowledge transfer methods can align the distributions of data or transfer relationships between frequency points. This allows spectrum sensing, interference identification, and anomaly detection models to be migrated between deployment sites with only limited retraining, thus providing the necessary flexibility for real-time spectrum monitoring.

C. SEI of Wireless Communication

SEI is fundamental to device authentication and unauthorized transmitter detection. A practical challenge lies in the fact that channel, receiver, and noise levels rarely match in training and deployment environments. However, RFFs can be used as domain-invariant features or information about relationships between transmitters, thus achieving reliable and accurate identification across different environments through knowledge transfer.

D. Uncrewed Autonomous Driving

Uncrewed Autonomous Driving perception must generalize to rare weather, unfamiliar road layouts, and new sensor configurations. Rather than relying on exhaustive labeling, knowledge transfer reuses

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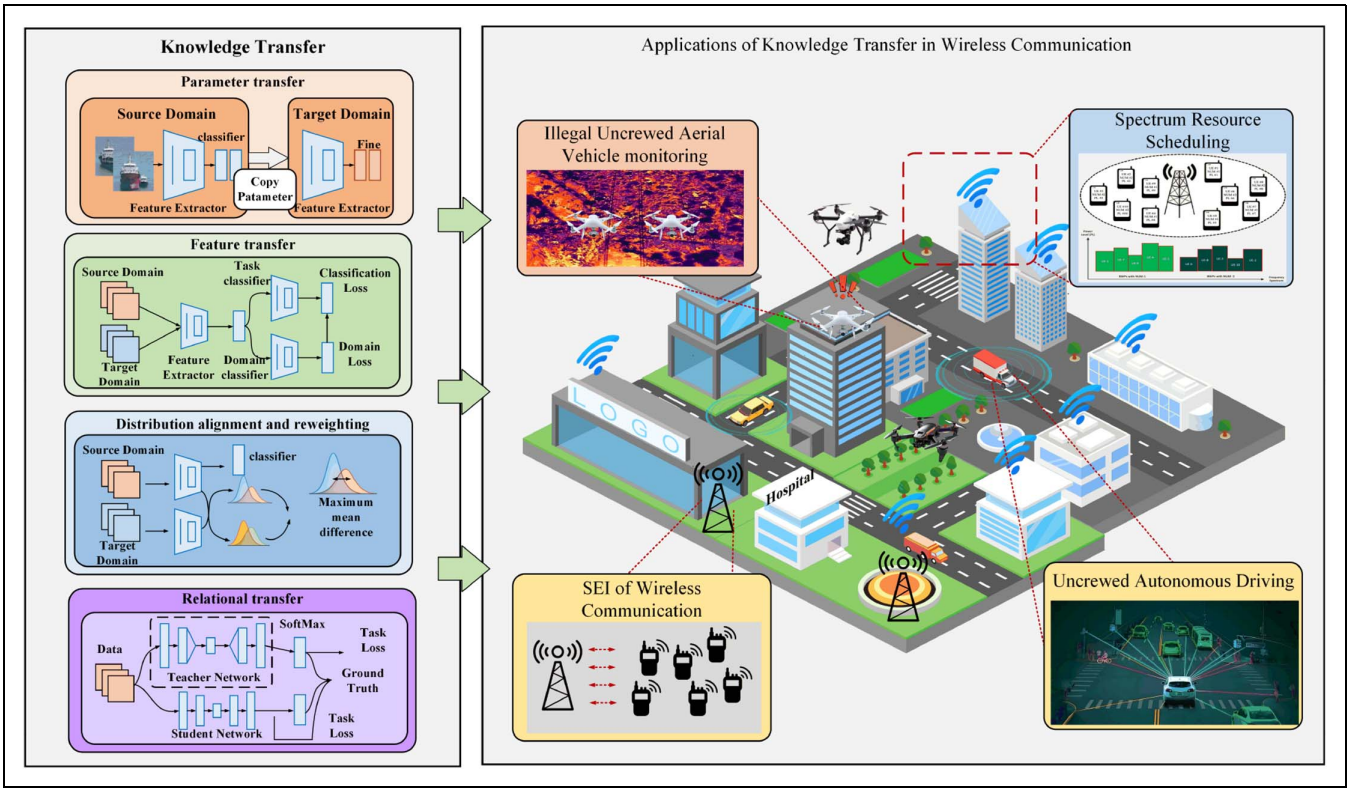


FIG. 2. The main methods of knowledge transfer and their applications in the field of communications. The left panel presents four representative knowledge transfer paradigms, namely parameter transfer, feature transfer, distribution alignment and reweighting, and relational transfer. The right panel shows their potential applications in wireless communication, including illegal UAV monitoring, SEI, spectrum resource scheduling, and autonomous driving. These examples indicate that knowledge transfer can reuse source-domain knowledge to improve model generalization, reduce dependence on labeled target-domain data, and support robust wireless intelligence in heterogeneous and dynamic communication environments.

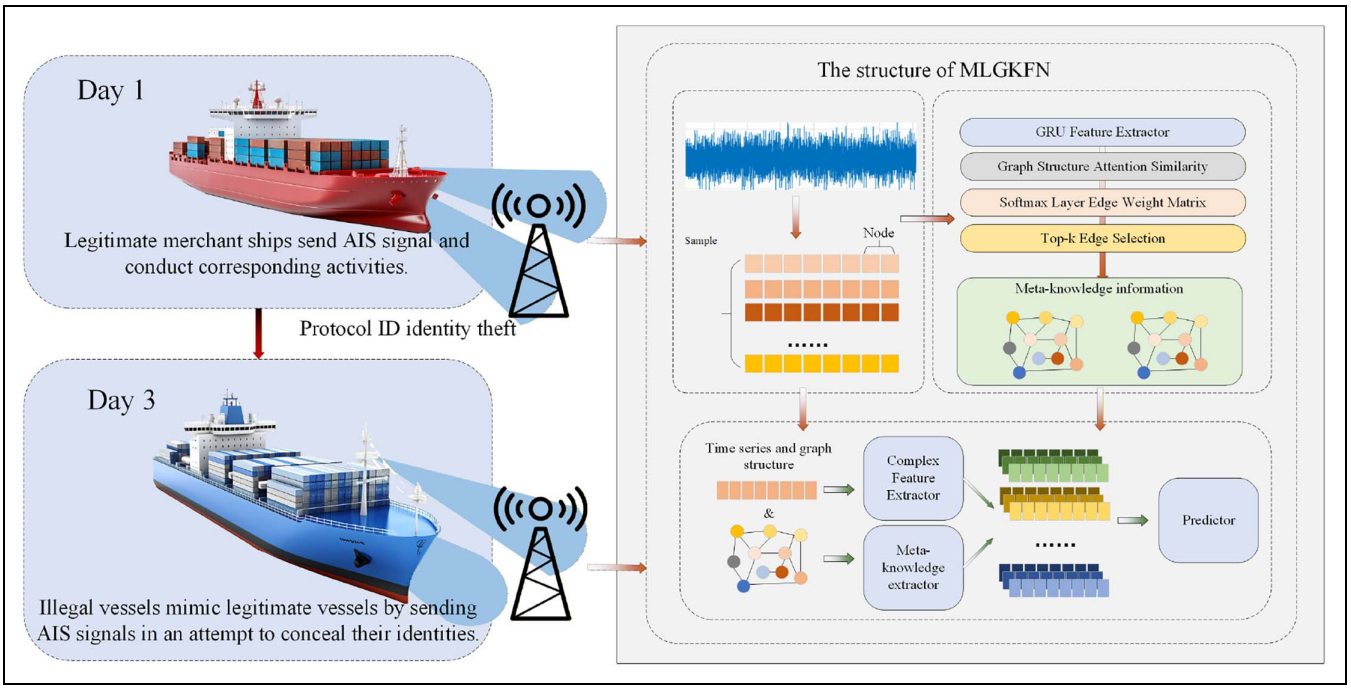


FIG. 3. SEI of maritime AIS signals based on the MLGKFN scenario. The figure illustrates an AIS identity-spoofing scenario, where legitimate ships transmit signals on Day 1 and adversaries may forge protocol IDs on Day 3. MLGKFN extracts time-frequency RFF features from segmented I/Q signals and represents them as graph nodes, while attention-based similarity and Top-k selection construct weighted edges between related samples. Meta-knowledge represents the learned adaptation prior over stable RFF relationships, which guides gradient-based updates using a few labeled target-domain samples. The refined time-series and meta-knowledge features are then fused for final emitter identification.

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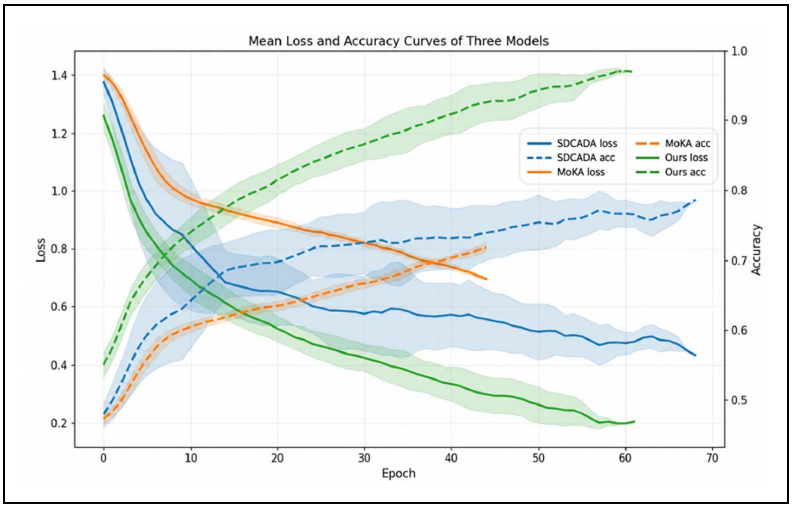


FIG. 4. Training loss and accuracy of the three models on the Day 1 source-domain training set over 10 independent runs. Curves show the mean values, and shaded regions denote standard deviation.

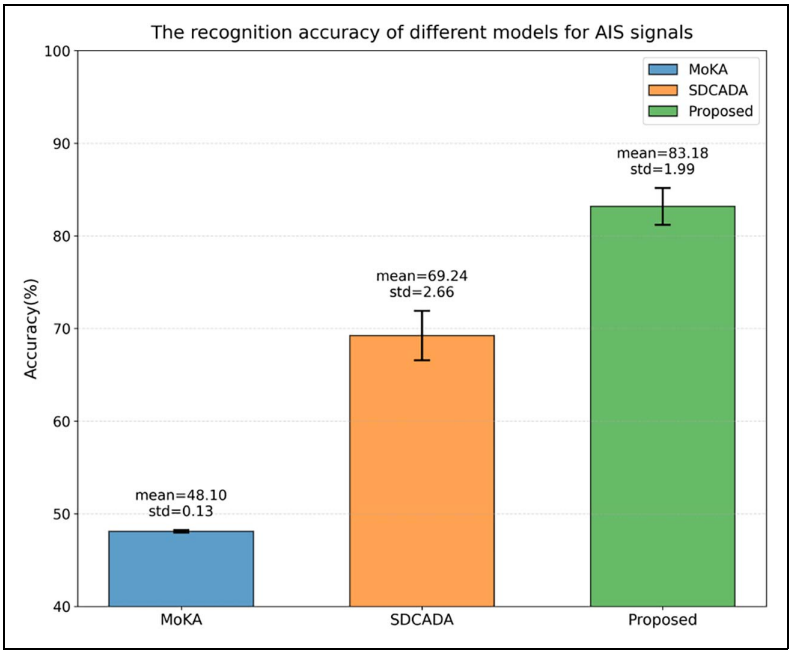


FIG. 5. The recognition mean accuracy (mean) and standard deviation (std) of different models for AIS signals after transferring.

representations learned from prior scenes and tasks, enabling rapid adaptation of detection, segmentation, and scene-understanding modules. This is a key enabler for safe deployment in long-tail traffic conditions where collecting representative training data is infeasible.

IV. Meta-Learning-Guided Knowledge Transfer Framework for SEI

In practical wireless monitoring and communication security, SEI relies on RFFs caused by hardware imperfections. However, changes in channel, noise, or receiver conditions can shift the target-domain signal distribution, making reliable identification difficult with only a few labeled I/Q samples. Unlike conventional pre-train-and-fine-tune transfer learning, meta-learning aims to enable rapid adaptation to new environments.

The proposed MLGKFN combines wireless prior knowledge with relational signal structures by constructing an RFF graph, where nodes represent signal segments and edges capture their similarities. Meta-knowledge represents adaptation experience rather than a physical component or mathematical variable, guiding the model to identify reliable RFF features and sample relationships under channel changes and adapt them using only a few labeled samples.

Each 1,024-point I/Q is encoded into eight signal-dependent node embeddings. Rather than relying on a predefined adjacency matrix, MLGKFN dynamically constructs the RFF graph from the current node representations. Specifically, the graph relations are obtained as

$$s_{ij} = \frac{\mathbf{q}_i^T \mathbf{k}_j}{\sqrt{d}}, \tilde{A}_{ij} = \begin{cases} \dfrac{\exp(s_{ij})}{\sum_m \exp(s_{im})}, & j \in \mathrm{TopK}_3, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where s_{ij} denotes the unnormalized attention score measuring the RFF-related similarity between nodes i and j. $\mathbf{q}_i$ and $\mathbf{k}_j$ are the query and key representations projected from the signal-dependent embeddings of nodes i and j, respectively, and d is their embedding dimension. $\tilde{A}_{ij}$ denotes the sparsified edge weight, where Top-k selection with $k = 3$ retains the three strongest relations for each node. Finally, symmetrization yields the sparse adjacency matrix $\mathbf{A} = (\tilde{\mathbf{A}} + \tilde{\mathbf{A}}^T)/2$. Thus, the graph structure is dynamically constructed from each input rather than predefined.

The Complex Feature Extractor applies STFT to obtain time-frequency features, which are modeled by a 6-layer GRU with hidden dimension 8. Relational features from the dynamic RFF graph are fused with temporal features through a learnable sigmoid gate and classified by a five-layer convolutional predictor. During Day 1 episodic meta-training, each task $\mathcal{T}_i = \{\mathcal{S}_i, \mathcal{Q}_i\}$ contains disjoint support and query sets. In the inner loop, the graph-generation module is fixed, while the adaptive modules are updated on $\mathcal{S}_i$ for five gradient steps with learning rate 0.01. In the outer loop, query losses over two tasks are averaged to update the meta-parameters with Adam at learning rate 0.001. Cross-entropy loss and early stopping are used for up to 500 epochs.

In summary, unlike generic GNNs operating on predefined graphs, MLGKFN dynamically reconstructs sparse RFF relations from signal-dependent node embeddings. Its encoder, relational, fusion, and prediction modules are meta-optimized for rapid few-shot adaptation. Thus, unlike prototypical learning based mainly on class-level prototypes, generic meta-learning without explicit RFF relations, or conventional pre-train-and-fine-tune transfer, MLGKFN jointly models sample-level RFF relations and cross-environment adaptation.

V. Case Study

In this section, we conduct a case study to evaluate MLGKFN for ship identification in a port scenario as in Fig. 3.

A. Scenario Description

We consider a scenario where a shore-based base station receives AIS signals transmitted by ships entering and departing a port. AIS messages include a Maritime Mobile Service Identity (MMSI) field, this field

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was removed before model input. These signals are used to train our network, constructing meta-knowledge and a graph structure to establish an intrinsic connection between the ship and the transmitter. As illustrated in Fig. 3, the framework includes an application scenario and a model-processing path. In the application scenario, RFFs are used to verify the true ship identity even when an adversary forges the MMSI. In the model path, I/Q signals are encoded into time-frequency features, used to construct an RFF graph, and then refined through meta-knowledge-guided adaptation with a few target-domain samples. Here, the "complex feature extractor" denotes the temporal-frequency encoder, while the "meta-knowledge extractor" refers to the graph construction and episodic adaptation module.

B. Dataset and Baseline Methods

This experiment used AIS signals from five ships. During processing, the MMSI codes were removed from the signals. The AIS signals consisted of complex baseband I/Q signal segments; due to the limited number of signals per ship, random slicing was performed to generate segments, with each segment containing 1,024 samples as the model input. Data collection spanned three days. As daily docking times varied among the ships, the volume of collected data differed, resulting in approximately 20 to 50 original signal samples per ship. After preprocessing and segmentation, samples from Day 1 were used for training, Day 2 a validation subset (60% samples) which is used only for hyperparameter selection and selected $K = 10$ balance samples from the remaining of each ship as support samples which were used only for few-shot adaptation, and all hyperparameters were fixed before Day 3 testing. Specifically, the imbalance sample counts of training, validation, and testing samples for the five ships were 262, 120, 420 for ship 1, 266, 121, 392 for ship 2, 380, 122, 483 for ship 3, 231, 121, 597 for ship 4, and 1004, 1821, 1754 for ship 5.

To evaluate the performance of the proposed method, we selected transfer learning and domain adaptation approaches for comparison. These two baseline models represent the most common paradigms in transfer learning: parameter fine-tuning and distribution-alignment-based domain adaptation. The transfer learning baseline assessed the effectiveness of adapting pre-trained model weights to the target AIS recognition task, while the domain adaptation baseline evaluated the efficacy of aligning data distributions across different collection days. By comparing these baselines, we further assessed whether the relational meta-learning strategy of MLGKFN could more effectively leverage transferable knowledge from the limited AIS samples.

- **MoKA** [14]: MoKA is a parameter-efficient transfer method based on Kronecker-product adapters. In the structure of MoKA, we use the same time-frequency backbone as MLGKFN and insert Kronecker adapters. We also use the same optimizer, learning rate as MLGKFN. The model is pre-trained on Day 1, using the same validation subset and support subset as MLGKFN from Day 2. The adapted model is then evaluated on Day 3 samples.
- **SDCADA** [15]: SDCADA is a domain adaptation method for cross-domain time-series classification. To adapt SDCADA to AIS-based SEI, the complex I/Q signal is represented as two real-valued channels. We also use the same optimizer and learning rate. Consistent with MLGKFN and MoKA, training was conducted using datasets processed in the same manner.

All methods used the same data partitions, support samples, tuning protocol, and training budget of up to 10 GPU-hours per model on an NVIDIA GeForce RTX 5060 Ti, with no additional data augmentation. Their total parameter counts are 208,645, 862,725, and 1,150,679 for MLGKFN, MoKA, and SDCADA, respectively.

C. Performance Evaluation

Fig. 4 shows the loss and accuracy curves during the training process of the three models. The proposed method achieves over 95% accuracy with stable fluctuations (shaded area), indicating that the episodic meta-training objective provides a smooth optimization landscape for the source-domain task. SDCADA exhibits greater standard deviation across runs, which may be attributed to the sensitivity of its distribution alignment losses to the random initialization and mini-batch composition. MoKA shows minimal fluctuation but the lowest accuracy, indicating that its adapter structure does not effectively capture RFF characteristics when the majority of backbone parameters are frozen.

Fig. 5 shows the models trained on the data collected on Day 1 and evaluated on the data collected on Day 3. MLGKFN achieves the best performance with 83.18% accuracy, outperforming SDCADA (69.24%) and MoKA (48.10%). The performance advantage is consistent with the intended benefits of graph-based relational modeling and episodic meta-learning. However, the current conclusions are based on only five ships over three days with a single receiver setup and require further validation in larger and more diverse scenarios.

VI. Conclusion

In this article, we reviewed the foundations, methodological categories, and representative wireless applications of knowledge transfer, and highlighted its importance for SEI under limited labeled data and severe cross-domain shifts. The discussion showed that parameter transfer, feature transfer, distribution alignment and reweighting, as well as relational transfer, each provide useful mechanisms for improving robustness and adaptation, but also face limitations when channel conditions vary significantly. We further emphasized that meta-learning offers a more suitable paradigm for SEI, since it transfers not only features or parameters, but also the adaptation strategy itself, enabling rapid calibration with only a few target-domain samples. On this basis, we presented the proposed MLGKFN, which integrates wireless prior knowledge, RFF characteristics, and graph-based relational modeling to enhance recognition under heterogeneous environments. However, this case study still has limitations. Future work needs to address the restricted scale and scenario diversity of the experiments, and the model's generalization capability requires further validation in larger-scale, more complex scenarios involving cross-environment and cross-protocol settings.

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Biographies

Zherui Zhang was born in Hebei, China, in 1999. He received the B.Eng. degree in 2021 from Harbin Engineering University, China, where he is currently working toward the Ph.D. degree. His primary research interests include specific emitter identification (SEI) based on electromagnetic signals and the adaptability of deep learning (DL) across different channel environments.

Shuang Li received the B.S. degree from the North University of China, Taiyuan, China, in 2019, and the Ph.D. degree from Harbin Engineering University, Harbin, China, in 2026. She is currently with Inspur Electronic Information Industry Company Ltd., Jinan, China. Her research interests include electromagnetic environment data mining, electromagnetic spectrum predictions, and knowledge transfer for intelligent agents.

Yinqiu Liu received the B.Eng. degree from Nanjing University of Posts and Telecommunications, China, in 2020, the M.Sc. degree from the University of California, Los Angeles, USA, in 2022, and the Ph.D. degree from Nanyang Technological University (NTU), Singapore. He is currently a Postdoctoral Research Fellow with NTU. His current research interests include blockchain security, mobile AIGC, and generative AI.

Bin Ge received the Ph.D. degree in mathematics from Harbin Institute of Technology, Harbin, China, in 2010. From 2011 to 2013, he was a Postdoctoral Researcher with Harbin Engineering University. Since 2013, he has been an Professor with Harbin Engineering University, Harbin. His research interests include nonlinear control theory and applications of control to automotive powertrain systems, and nonlinear analysis.

Qiling Gao (qilinggao@outlook.com) received the B.S. degree from Harbin Engineering University, China, and the Ph.D. degree from Harbin Institute of Technology, China. During her doctoral studies, she was a joint Ph.D. student with the University of Southampton, U.K. She is currently a Lecturer with Harbin Engineering University. Her research interests include integrated space–air–ground–sea communication networks and multiple access technologies.

Yun Lin (Senior Member, IEEE) received the B.S. degree from Dalian Maritime University, Dalian, China, in 2003, the M.S. degree from Harbin Institute of Technology, Harbin, China, in 2005, and the Ph.D. degree from Harbin Engineering University, Harbin, in 2010. He was a Research Scholar with Wright State University, USA, from 2014 to 2015. He is currently a Full Professor with the College of Information and Communication Engineering, Harbin Engineering University. His research interests include machine learning and data analytics over wireless networks, signal processing and analysis, cognitive radio, and software-defined radio.

Giorgio Taricco (Fellow, IEEE) received the Laurea degree (*cum laude*) in ingegneria elettronica from the Politecnico di Torino, Italy, in 1985. He was a Researcher with the Italian Telecom Laboratories (CSELT), Italy, from 1985 to 1987, where he was involved in the design process of the GSM mobile telephony standard (channel coding). Since 1991, he has been with the Department of Electronics and Telecommunications (DET), Politecnico di Torino, as an Assistant Professor, where he has been a Full Professor since 2010. In 1996, he was a Research Fellow with ESA/ESTEC, The Netherlands. He has coauthored more than 200 papers published in international journals and international conferences, several book chapters, and three international patents. His research interests include information theory, error-control coding, multiuser detections, space-time coding, MIMO communications, cognitive radio networks, sensor networks, the IoT satellite networks, and MIMO relay channels. He was a co-recipient of best paper awards from the WPMC 2001 Conference and the Journal of Communications and Networks (Special Issue on Coding and Signal Processing for MIMO Systems) in 2003. He was on the ISI highly cited researcher list in the category of computer science from 2008 to 2013. He has participated in several committees of IEEE conferences (as a Treasurer). He was a Senior Associate Editor of IEEE Wireless Communications Letters. He has been an Associate Editor of IEEE Communications Letters, IEEE Transactions on Information Theory, *Journal on Communications and Networks*, and *Entropy*.

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