

PDW Machine Learning for Distributed Wireless Spectrum Intelligence: A Survey and Federated Self-Supervised Roadmap

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Abstract—Modern electromagnetic environments are becoming increasingly dense, agile, and overlapping, creating new challenges for Pulse Descriptor Word (PDW)-based radar signal sorting and deinterleaving. Recent studies have moved beyond traditional Pulse Repetition Interval (PRI)-based search and rule-driven processing toward machine learning approaches based on sequential Transformer models, graph-based hybrid models, image-like mappings, point-cloud formulations, and PDW-specific embeddings. This paper provides a compact representation-centric survey of recent PDW machine learning approaches and examines their relevance to distributed wireless spectrum intelligence. In particular, this survey reviews major representation families for PDW-based deinterleaving, examines distributed and multi-station PDW sensing studies, and connects these trends with federated and self-supervised learning. This survey identifies federated self-supervised PDW representation learning as a promising research direction for practical sensing environments in which receiver observations are heterogeneous, pulse-level labels are limited, and raw data sharing is undesirable.

Index Terms—Pulse Descriptor Word (PDW), radar signal deinterleaving, signal sorting, federated learning, self-supervised learning, distributed wireless spectrum intelligence.

I. INTRODUCTION

Radar signal deinterleaving is a core step in electronic support, spectrum monitoring, and emitter-aware wireless sensing. In dense electromagnetic environments, a receiver observes an interleaved pulse stream generated by multiple radar sources, and each pulse is typically summarized by a Pulse Descriptor Word (PDW), including time-of-arrival (TOA), radio frequency (RF), pulse width (PW), pulse amplitude (PA), and angle-of-arrival (AoA) information. The objective is to separate the interleaved stream into emitter-specific pulse groups or pulse trains.

Classical deinterleaving methods rely on handcrafted rules, histogram analysis, Pulse Repetition Interval (PRI) search, clustering, and expert-driven parameter association. These methods remain useful under simple emitter patterns and

controlled signal conditions, but they become less reliable under agile radar operation, complex PRI modulation, missing or spurious pulses, dense interleaving, parameter overlap, and receiver-dependent observation bias. Recent studies have therefore reformulated PDW deinterleaving as a machine learning problem based on sequence modeling, metric learning, graph learning, semantic segmentation, point-cloud segmentation, and descriptor-specific embedding. This shift suggests that PDW deinterleaving should be understood not only as rule-based sorting, but also as representation learning over pulse descriptor structures and pulse-to-pulse relations.

Practical sensing systems are often distributed. Multiple receivers may observe different subsets of emitters under different antenna coverage, propagation conditions, interference levels, and sensing windows. As a result, each receiver can have a different local PDW distribution, while centralizing all raw observations may be costly or operationally undesirable. In addition, pulse-level labels are expensive to obtain and difficult to verify in realistic environments. These constraints motivate learning frameworks that can exploit distributed observations while reducing dependence on labeled data and raw data sharing.

In this paper, we view distributed wireless spectrum intelligence as PDW-oriented sensing and analysis over local spectrum observations collected by distributed receivers. Within this scope, federated learning (FL) and self-supervised learning (SSL) provide complementary perspectives: FL supports distributed model training without directly pooling raw observations, while SSL can learn useful representations from unlabeled pulse streams. This paper provides a compact representation-centric survey of recent PDW machine learning studies, connects distributed and multi-station PDW sensing with the motivation for FL, and identifies federated self-supervised PDW representation learning as a promising direction under receiver-wise non-independent-and-identically-distributed (non-IID) observations, label scarcity, descriptor preservation requirements, and reliability concerns.

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II. BACKGROUND AND SCOPE

PDW-based radar pulse deinterleaving aims to separate an interleaved pulse stream into pulse groups originating from the same emitter. This problem can be viewed as a combination of pulse-level classification, clustering, pulse train reconstruction, and emitter grouping. In practical settings, the number of emitters may be unknown, and different emitters may exhibit overlapping RF, PW, PRI, or AoA patterns. Under such conditions, simple thresholding is often insufficient for robust separation.

A raw PDW record typically contains measured descriptors such as TOA, RF or carrier frequency (CF), PW, PA, and AoA or direction-of-arrival (DOA). Inter-pulse temporal quantities, such as the difference between adjacent TOA values (DTOA) or PRI-related features, are usually derived from the TOA sequence rather than being treated as raw pulse descriptors. Because these measured and derived descriptors have different physical meanings and numerical scales, normalization, embedding, and relation modeling are important in PDW representation learning.

For learning, a pulse-level feature vector can be written as

$$\mathbf{x}_i = [t_i, f_i, w_i, a_i, \theta_i, \Delta t_i]^\top, \quad (1)$$

where t_i , f_i , w_i , a_i , and θ_i denote measured descriptors corresponding to TOA, RF/CF, PW, PA, and AoA/DOA, respectively. The term Δt_i denotes a derived temporal feature computed from neighboring TOA values; PRI-related quantities can also be estimated from the TOA sequence when pulse-train structure is available. Additional descriptors, such as modulation type, signal type, or confidence scores, can be included when available.

An interleaved pulse stream can be denoted by $\mathcal{X} = \{\mathbf{x}_i\}_{i=1}^N$, and deinterleaving aims to assign each pulse to an emitter or source group. Since the number of emitters may be unknown or time-varying in real environments, PDW-based deinterleaving is closely related not only to supervised classification but also to clustering, segmentation, and representation learning.

PDW-based deinterleaving is related to RF fingerprinting and specific emitter identification (SEI), but it is not the same task. SEI and radio frequency fingerprint identification (RFFI) typically focus on identifying transmitter identity from raw in-phase/quadrature (I/Q) signals or device-specific RF impairments. In contrast, PDW deinterleaving operates on extracted pulse descriptor sequences and asks which pulses belong to the same emitter-specific pulse train.

Accordingly, SSL in SEI/RFFI can be understood as learning label-efficient RF fingerprint representations. In PDW deinterleaving, however, the learning process must also account for structured descriptors and temporal pulse relations, including measured descriptors such as TOA, RF, PW, PA, and AoA, as well as derived temporal quantities such as DTOA or PRI-related features. Existing SSL-SEI surveys are important for organizing RF fingerprint-based emitter identification, but their scope differs from a survey focused on PDW sequence

deinterleaving, multi-station sensing, and federated PDW representation learning [1].

This paper focuses on a representation-centric view of recent PDW machine learning studies. While existing reviews provide broader coverage of classical and deep learning-based radar signal deinterleaving methods [2], this survey organizes recent PDW approaches by input representation and model structure, and identifies open issues for federated self-supervised PDW representation learning.

III. A REPRESENTATION-CENTRIC TAXONOMY OF PDW MACHINE LEARNING

Recent PDW machine learning studies have evolved along several representation and model-design directions. This section groups them into five categories: sequence/Transformer models, graph and hybrid temporal-structural models, image-like mappings, point-cloud representations, and PDW-specific embeddings. Table I summarizes their main ideas, strengths, and limitations.

A. Sequence and Transformer-Based Approaches

The most direct approach treats PDWs as a TOA-ordered sequence and applies sequential models. Radar pulse streams have temporal order, and pulses from the same emitter may share temporal and descriptor relations, such as PRI regularity, RF transition patterns, PW consistency, and AoA stability. Recurrent neural networks and Transformers are therefore natural candidates for modeling pulse-to-pulse dependencies.

A Transformer-based deep metric learning study learns pulse embeddings and then forms emitter-specific pulse groups through clustering [3]. This approach is important because it connects representation learning with deinterleaving settings in which the number of emitters is not known in advance. Another study augments limited PDW descriptors, such as carrier frequency (CF), PW, and PA, by generating hypothetical modulated signals and applying a Transformer-based model, thereby reducing reliance on PRI information [4]. A further Transformer-based sorting method combines learnable positional encoding with a modified self-attention mechanism to strengthen pulse sequence relationships under parameter overlap and missing-pulse conditions [5].

The main advantage of this family is its ability to model pulse order and long-range temporal dependencies. However, many of these methods still rely on pulse-level labels or metric-learning supervision, and their generalization under receiver-wise non-IID sensing environments remains insufficiently studied.

B. Graph and Hybrid Temporal-Structural Modeling

A PDW sequence contains not only temporal order but also structural relations among pulses. Pulses from the same emitter may exhibit consistent relations in RF, PW, PA, AoA, or DTOA. Such relations can be represented as a graph. Graph-based and hybrid models can therefore complement sequence models by explicitly modeling attribute-level pulse relations.

TR-RAGCN-AFF-RESS extracts temporal patterns from PDW sequences using a Transformer, constructs attribute-similarity graphs from RF/PW/PA/DOA, and learns structural pulse relations through a Graph Convolutional Network (GCN)-based model before fusing the two feature streams [6]. This method can be viewed as an example of attention-based fusion between temporal features and attribute-graph features for pulse-by-pulse sorting.

Graph and hybrid approaches are attractive because they can explicitly encode pulse relations. However, their performance can depend on how neighboring pulses are selected and how edge weights are assigned. In distributed receiver settings, the observed pulse subset and signal condition may differ across receivers, which means that the local graph structure itself can become receiver-dependent.

C. Sequence Semantic Segmentation and Image-Like Mapping

Segmentation-based PDW studies do not all use the same input form. The semantic segmentation deinterleaving (SSD) study reformulates radar signal deinterleaving as an equal-length sequence labeling problem: DTOA sequences are fed into BGRU, BLSTM, or dilated convolutional network (DCN) models, and a semantic category is assigned to each pulse [7]. This formulation avoids explicit PRI search and can handle complex PRI modulation, pulse loss, and noise pulses, but it is closer to sequence semantic segmentation than to image-like mapping.

Other studies convert PDWs or pulse relations into image- or matrix-like representations and then apply segmentation frameworks. A PDW dot-matrix-image-based study converts PDW data into a two-dimensional (2D) dot matrix image and uses the authors' Cascade-Recurrent Loop Network (CRLN) to estimate the number of sources and recurrently segment individual radar sources [8]. Sep-RefineNet constructs a Frequency Characteristic Matrix (FCM), which encodes the occurrence frequencies of PRI candidates derived from TOA information, and uses a semantic segmentation network to decode pulse positions [9]. Antenna Scan Pattern (ASP)-based mimetic image mapping converts PDW attributes such as TOA, PA, and CF into point coordinates and colors in a 2D image and then applies the public SOLOv2 instance segmentation model to separate pulse groups [10].

These segmentation-based approaches benefit from dense prediction or mature visual segmentation frameworks. However, sequence semantic segmentation depends on how radar semantics are defined, while image-like mappings may distort temporal resolution, descriptor scales, and sparse pulse relations. Consequently, the performance of these methods can be sensitive to the semantic definition, mapping rule, and resolution setting.

D. Point-Cloud Representation

Point-cloud representation maps each pulse into a point in a three-dimensional or multidimensional PDW feature space and reformulates deinterleaving as point-cloud segmentation. This formulation can directly exploit sparse geometric relations

more naturally than dense image-like mappings and is suitable for modeling feature-space proximity and local pulse structure.

A point-cloud-mapping-based study converts PDWs into point clouds and uses a segmentation network in which multiple GCN layers progressively aggregate and update neighboring pulse features, thereby separating densely interleaved pulses by emitter [11]. This approach avoids the dense grid constraint of image representations while still exploiting geometric relations.

Nevertheless, point-cloud mapping remains sensitive to feature selection, axis design, normalization, and the encoding of temporal information.

E. PDW-Specific Embedding and Value-Aware Representation

Recent work has also raised the concern that generic embeddings or simple normalized inputs may not fully capture the characteristics of PDW data. WVEmps with masking is an arXiv preprint that converts wide-range and heterogeneous PDW features into dedicated embedding vectors and masks parts of the embedding dimensions to generate harder training samples for improving learning stability and robust feature learning in radar signal sorting [12]. At this stage, it is better viewed as an early example highlighting the need for PDW-specific embedding design rather than as an established standard method.

The key motivation for PDW-specific embedding is that RF, PW, PA, AoA, and TOA/DTOA have different physical scales and distributions. Treating all descriptors in the same way can weaken the structural meaning of some features. Value-aware and descriptor-aware representations may therefore play an important role in future PDW SSL and FL studies.

IV. FROM DISTRIBUTED PDW SENSING TO FEDERATED LEARNING

A. Distributed and Multi-Station PDW Sensing

The observation of a single receiver can vary with its location, antenna coverage, propagation environment, interference, terrain or structural blockage, and sensing time window. Therefore, in a practical sensing network, each receiver may observe a different local PDW distribution.

Let $\mathcal{D}_k$ denote the local PDW observations collected by receiver k . In some supervised settings, an emitter assignment $g_i^{(k)}$ may be available, but in practical environments such labels are often limited or incomplete. Since receiver locations and observation conditions differ, it is unrealistic to assume that all receivers follow the same local data distribution. A receiver-wise non-IID condition can be expressed as

$$P_k(\mathbf{x}) \neq P_\ell(\mathbf{x}), \quad k \neq \ell. \quad (2)$$

This notation does not assume a specific FL algorithm, but it highlights that local observation heterogeneity is a central issue in distributed PDW learning. These conditions extend radar signal sorting from a centralized single-station processing problem to a distributed observation and information fusion problem.

TABLE I
REPRESENTATION-CENTRIC TAXONOMY OF PDW MACHINE LEARNING APPROACHES

Category	Input representation	Main idea	Strength	Limitation
Sequence / Transformer	TOA-ordered PDW sequence	Temporal dependency modeling	Captures temporal patterns	Label dependence
Graph / Hybrid	Pulse relation graph and sequence	Temporal-structural fusion	Captures pulse relations	Sensitive graph design
Segmentation / Image-like	DTOA sequence, PDW matrix, dot image, or mimetic map	Sequence/image segmentation	Dense pulse labeling	Sensitive mapping rules
Point Cloud	Geometric PDW points	Point-cloud segmentation	Uses geometric structure	Mapping-dependent
PDW-Specific Embedding	Descriptor-aware value embedding	Descriptor-aware embedding	Handles descriptor heterogeneity	Emerging direction

An information fusion study with distributed reconnaissance receivers combines locally computed decisions and confidence evidence to mitigate the vulnerability of centralized fusion [13]. A multi-station cooperative radar signal deinterleaving study further uses pulse sequences from multiple stations and proposes a deep information fusion approach for separating close-parameter and imbalanced signals more effectively [14].

These studies indicate that PDW sensing is naturally connected to distributed and multi-station settings. However, the reviewed distributed and multi-station PDW studies mainly focus on fusion rules, decision fusion, or deep information fusion, rather than systematically addressing local model learning and global representation aggregation from a federated learning perspective.

B. Why Federated Learning Is Relevant

Federated learning is a framework in which local clients or receivers train models using their own observations and participate in global aggregation without directly transferring raw data to a central server. In PDW sensing, FL is relevant for three reasons.

First, centralizing raw PDW streams can incur substantial communication costs and operational security concerns. Second, each receiver may observe a different emitter subset, signal-to-noise ratio (SNR) condition, AoA distribution, or pulse loss pattern, making the independent and identically distributed (IID) assumption unrealistic. Third, pulse-level labels are costly to generate and verify, limiting the scalability of supervised-only learning in deployment.

Therefore, in PDW machine learning, FL can be interpreted as more than a privacy-preserving training tool. It provides a framework that reflects the structural characteristics of distributed sensing environments under receiver-wise heterogeneity, as expressed in Eq. (2). More broadly, communication-efficient distributed learning has been studied in the wireless learning literature as a way to jointly address limited wireless resources, time-varying channels, and heterogeneous clients [15]. Communication-efficient FL studies based on multi-width or slimmable neural networks further show that aggregation and model adaptation should account for poor channel conditions, non-IID data, and client resource heterogeneity in wireless FL systems [16], [17].

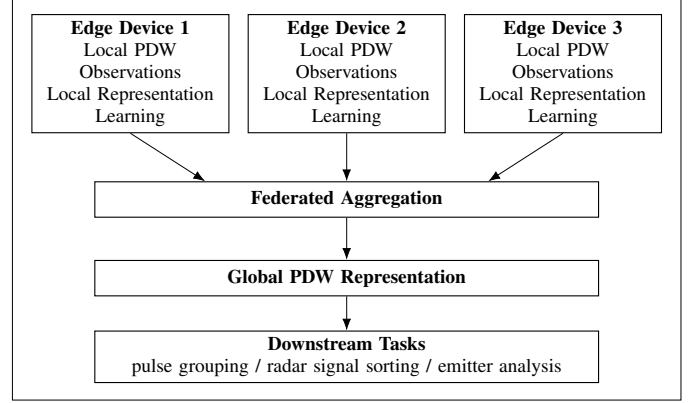


Fig. 1. A conceptual flow of federated self-supervised PDW representation learning in distributed sensing, where each edge device collects local PDW observations and performs local representation learning before federated aggregation.

C. Connections to SSL and FL in RF/SEI/RFFI

Federated self-supervised learning for PDW deinterleaving remains underexplored in the reviewed literature, but related trends have already appeared in adjacent RF signal intelligence domains. In RFFI, unsupervised contrastive learning has been combined with federated learning to address receiver hardware and location variations [18]. In SEI, feature imitation and alignment have been used in a federated learning setting to mitigate data heterogeneity and global model drift under low-resource conditions [19]. Few-shot SEI and RF signal classification studies also suggest that SSL can reduce label scarcity in wireless signal representation learning [20], [21].

These studies do not solve the same task as PDW deinterleaving. Nevertheless, they share common concerns, including label scarcity, distributed learning, receiver variation, and signal representation learning. Thus, SSL/FL studies in RF, SEI, and RFFI can serve as adjacent research streams that support the need for federated self-supervised PDW representation learning. At the same time, PDW data contain structured pulse descriptors and pulse grouping relations, requiring PDW-specific learning objectives and evaluation protocols that differ from RF fingerprint representation.

D. Conceptual Roadmap

Fig. 1 summarizes a model-agnostic pipeline from local PDW observations to local representation learning, federated

aggregation, and downstream tasks such as pulse grouping, signal sorting, and emitter analysis.

V. KEY CHALLENGES AND RESEARCH DIRECTIONS

Several open issues remain for federated self-supervised PDW representation learning. Pulse-level or emitter-level labels are costly to obtain, and ground-truth verification becomes more difficult under complex inter-pulse modulation and parameter overlap [22]. This motivates PDW-specific SSL objectives that can learn from unlabeled pulse streams while preserving temporal pulse relations and descriptor semantics.

Distributed receivers naturally induce receiver-wise non-IID observations, where local data distributions may differ by emitter coverage, AoA range, SNR condition, pulse loss pattern, and sensing window. Evaluation should jointly consider local receiver performance, global representation quality, communication efficiency, label efficiency, unknown-emitter handling, descriptor preservation, and robustness to receiver-specific bias. Benchmark design should also account for missing or spurious pulses, communication cost, and deinterleaving performance. Recent benchmark efforts, such as the Turing Synthetic Radar Dataset, provide a useful starting point for standardized evaluation of unknown-emitter PDW deinterleaving [23].

VI. CONCLUSION

Recent PDW machine learning studies indicate a shift from rule-based sorting toward representation learning over pulse descriptor structures and relations, including sequence/Transformer, graph/hybrid, segmentation/image-like, point-cloud, and descriptor-specific embedding approaches.

However, many studies still rely on centralized learning and supervised labels, leaving receiver-wise non-IID observations, label scarcity, and raw-data sharing constraints underexplored. Distributed PDW sensing and adjacent SSL/FL studies in RF, SEI, and RFFI suggest a path toward label-efficient and data-decentralized signal representation learning.

Accordingly, federated self-supervised PDW representation learning is a promising direction for distributed wireless spectrum intelligence under receiver-wise non-IID observations, label scarcity, and raw-data sharing constraints. Future work should address PDW-specific SSL, descriptor preservation, benchmark design, and reliable evaluation.

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