Unsupervised Domain Adaptation Algorithms in Industrial Environments: Recent Advances and Current Applications

Tingkai Zhang
University of Macau, Macao, 999078, China
dc32829@um.edu.mo

ABSTRACT

In the complex industrial environment, the original physical properties, such as rotating speed and various machines, which change with time, will inevitably lead to unrecoverable feature changes and the decline in the extensive use of models. Therefore, unsupervised domain adaptation (UDA) is the basic structure to bridge the gap between intelligent diagnosis and practical use. However, most of the existing UDA summaries only illustrate the algorithms one by one, and there is no systematic investigation based on the fundamental principles of industrial constraints. Because of the fragmentation of this method, a huge gap has been formed between the most advanced theoretical discovery and its application in practical engineering. In order to break this deadlock, this summary completely abandons the past algorithm-centered classification method, establishes a new orthogonal separation framework, and directly deduces the solution method of abstract algorithm from specific physical constraints. Within this big framework, this paper arrangement illustrates the following four mechanisms. First, the dynamic structure fixing mechanism in the ever-changing state; Second, the feature remodeling without using the original features while protecting the privacy of cross-enterprise; Third, the complementarity and diversity generated in the cold start state with very few samples; Finally, the review advocates that the following three are the established evolution paths to promote the new generation of industrial intelligence to realize large-scale automated operation: third, The structure based on physics is added to the center of the algorithm, and the engineering structure is transferred to light edge computing, and Industrial Foundation Models are used to close the macro data and physics.

Keywords: Unsupervised Domain Adaptation; Intelligent Fault Diagnosis; Industrial Physical Constraints; Source-Free Adaptation; Lightweight Edge Computing; Industrial Foundation Models

1. INTRODUCTION

Deep learning technology shows strong fault diagnosis ability in closed test set, but its basic effect is bound by strict independent and identically distributed (IID) assumption. However, in the real world, when used in large-scale projects, physical equipment will be used for a long time. This state has the characteristics of speed changing with time, rapid load change and structural deviation across equipment. Due to these physical limitations, the real-time monitoring signal greatly deviates from the feature space of the original domain, and a large domain shift will inevitably occur, which greatly reduces the generalization ability of the model. In order to connect the discontinuity of this physical representation, unsupervised domain adaptation (UDA) fundamentally destroys the data constraints of traditional closed sets. By closely matching the distribution of original domain features with the distribution of unlabeled target domain features, UDA will create a powerful knowledge transfer path to cross operating conditions and equipment boundaries. Therefore, it has become the core basic mechanism to cross the gap of industrial intelligent diagnosis implementation.

Unsupervised domain adaptation has developed rapidly in the field of industrial intelligence, but the current research papers are still uneven in theory. The papers summarized now can be roughly divided into two kinds of ideas. The first idea is to focus only on the use of industrial fault diagnosis, and list many ways to use algorithm. However, I didn't deeply decompose the fundamental mechanism of feature alignment under extreme physical restrictions. The second idea is the recent survey of source free domain adaptation [1][2] is an example. The framework of abstract computational logic and privacy preservation is being investigated in depth. However, these investigations have fundamentally eliminated the complicated and time-varying machine movements that existed in the real-world environment. As a result, there is still an important method gap between the pure algorithm theory and the reality of industrial engineering.

In order to fill this basic gap, this comment deliberately does not use the classification of ordinary flat algorithm. The most important point of this study is divided into three different parts. Firstly, unlike the traditional survey of extensive and superficial application arrangement, this paper explicitly only extracts unsupervised domain adaptation as the core algorithm to fill the implementation gap under physical constraints. Secondly, unlike the current survey of source free domain adaptation only involving computational logic, this study has made a right-angled separation framework for the first time. This framework directly corresponds the working principle of abstract feature alignment with four specific physical problems. It consists of continuous time varying evolution, cross enterprise privacy isolation, extreme small sample cold starts, multi source heterogeneous conflicts, this review gives an evolutionary path consisting of three clear parts. In order to realize large-scale autonomous driving, physics informed mechanisms, lightweight edge computing and Industrial Foundation Models are summarized in Figure 1.

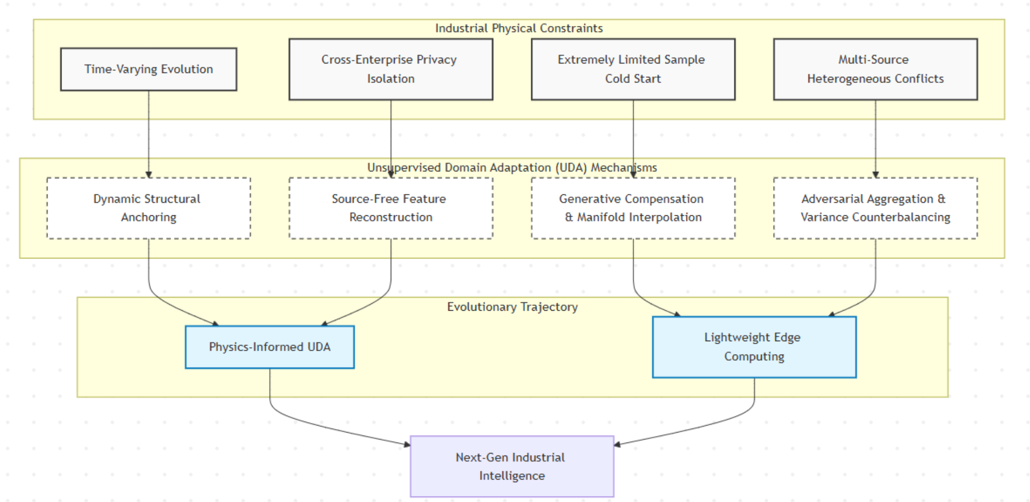

Figure 1. The proposed orthogonally decoupled framework for industrial unsupervised domain adaptation, systematically mapping core physical constraints to algorithmic mechanisms.

Finally, considering that the evolutionary trajectories is developing in the direction of combining physics-informed mechanisms with lightweight edge deployment, the review will discuss the new generation of intelligent diagnostics.

2. DECOUPLING UDA MECHANISMS FROM INDUSTRIAL PHYSICAL CONSTRAINTS

Before we begin to explain the algorithm in detail, Table 1 shows us the overall orthogonal decoupling matrix. The matrix examines the latest literature from 2021 to 2026 in order to better cope with the limitations of different UDA methodologies and their engineering and the main physical limitations of four industrial fields.

Table 1. Orthogonal Decoupling Matrix of UDA Mechanisms and Industrial Physical Constraints.

Industrial Physical Constraint	Representative Work (Method & Author)	Core Algorithmic Mechanism	Engineering Limitations / Evolutionary Role in This Review
1.Continuous Time-Varying Evolution	MLFDAN (Lin et al.,2025) [3]	Multi-level fusion across data, feature, and decision layers.	Focuses on static, discrete shifts; fails on serialized continuous streams.
	DCADAN (Wang et al., 2025) [4]	Dynamic collaborative adversarial network for multiple objectives.	Lacks structure-preserving and anti-forgetting mechanisms for long-term sequential adaptation.
	Continual-UDA (Lian et al., 2026) [5]	Continual UDA with structure-preserving probabilistic anchors.	Ultimate Solution: Dynamically tracks target streams, preventing catastrophic forgetting.

Table 1. (continued) Orthogonal Decoupling Matrix of UDA Mechanisms and Industrial Physical Constraints.

Industrial Physical Constraint	Representative Work (Method & Author)	Core Algorithmic Mechanism	Engineering Limitations / Evolutionary Role in This Review
2.Cross-Enterprise Privacy Isolation	SF-UDA (Wang et al.,2023) [6]	Source-free UDA via pseudo-label clustering & nearest-centroid filtering.	Addresses data invisibility but suffers statistical bias during extreme cold starts.
	Generative Self Tuning Mechanisms (Reviewed by Zhang et al., 2024) [1]	Source-free feature alignment and generative self-tuning framework.	Highly dependent on pre-trained model quality; struggles with multi-plant scaling.
	IDD-LUDA-FL (Ren & Li, 2026) [7]	Federated Learning integrated with lightweight dynamic UDA.	Ultimate Solution: Enables secure multi-plant collaborative parameter synchronization.
3. Extreme Small-Sample Cold Starts	DASAE (Fang et al., 2024) [8]	Stacked autoencoder combined with domain adversarial weighting.	Relies on existing sample availability; mode collapses under absolute feature voids.
	DCDM (Zhang et al., 2025) [9]	Domain-guided conditional diffusion models.	Ultimate Solution 1: Eradicates feature voids by generating high-fidelity samples from scratch.
	Deep-Subspace (Kumar et al., 2024) [10]	Subspace interpolation via deep transforms.	Ultimate Solution 2: Preserves intrinsic manifold geometry for small-sample robustness.
4.Multi-Source Heterogeneous Conflicts	Multiview-LSL (Zhu et al., 2024) [11]	Multiview latent space learning for multi-source adaptation.	Inaccurate pseudo-labeling under complex physical mappings triggers severe negative transfer.
	Distributed-GAN (Xu et al., 2021) [12]	Distributed adversarial training with exclusive domain discriminators.	Achieves global preliminary aggregation but ignores local fine-grained geometric boundaries.
	OUDA (Wang et al., 2024) [13]	Gradient adversarial adaptation & local manifold embedding.	Ultimate Solution: Rigorously balances invariance and variance, overcoming local feature confusion.

2.1 Dynamic Structural Anchoring under Continuous Time-Varying Evolution

The characteristics of unsteady behavior of rotating machinery are the core physical problems of industrial intelligent diagnosis. Therefore, it is absolutely necessary to solve the problem of model deterioration when it changes with time to use unsupervised domain adaptation (UDA) technology in engineering. When dealing with unlabeled and sequential data streams, the common single-shot static UDA model, which has been in the environment with large and continuous changes in speed and load for a long time, will always have feature deviation and the previously acquired diagnostic knowledge will be seriously forgotten. Lin [3] and Lian [5] also show this point. In view of the time-varying physical constraints, Lian [5] created a dynamic mapping standard in the framework of continual UDA. This is a probabilistic anchoring mechanism based on preserving structure. Using multi-component feature alignment and local topology conservation, this mechanism fixes the reference frames of data distribution in different evolution stages in the potential feature space. In this way, the knowledge obtained from continuous target data streams can be summarized, and the statistical and semantic consistency of cross-conditional feature distribution can be fully maintained. In particular, this probabilistic anchoring mechanism uses the momentum-based exponential moving average (EMA) method to continuously update the class-centric centroid. By constructing a local structure diagram based on the nearest neighbor in the feature space, the target domain feature of time step T mathematically conforms to the dynamic anchor established in time step t-1. This sort can prevent the weight of neural network from changing greatly in the latest data distribution, and effectively reduce the forgetting of past degradation patterns.

As shown in Figure 2, geometric analysis dynamically tracks the distribution of target stream to reduce destructive forgetting.

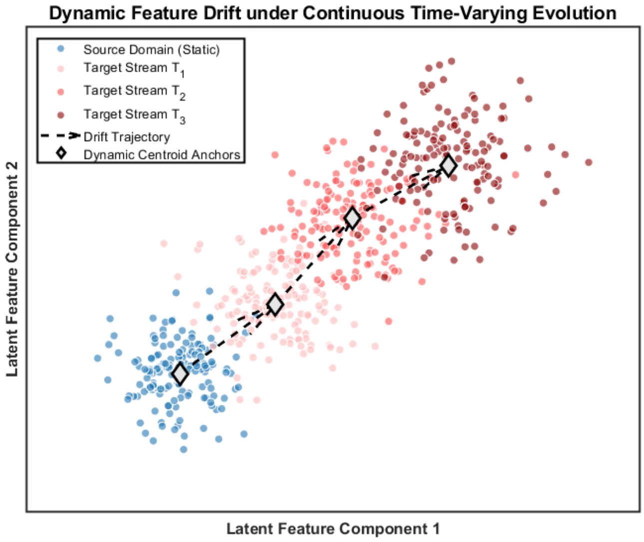

Figure 2. The dynamic feature drift trajectory and geometric centroid anchoring mechanism under continuous time-varying conditions.

Having conquered the sequential degradation driven by non-stationary physical evolution, dismantling the cross-enterprise privacy barriers induced by the physical isolation of multi-source equipment constitutes the subsequent logical node for extending UDA towards extremely constrained scenarios.

2.2 Source-Free Feature Reconstruction under Cross-Enterprise Privacy Isolation

The rules of protecting data privacy across enterprises and physically dividing data have become great obstacles in intelligent diagnosis used in industry. Therefore, the domain adaptive method in this field must be transformed from the method of calculating the data of two regions together to the source-free distributed structure. Especially, due to the strict confidentiality rules of electromechanical actuators and other important confidential parts in aerospace, the common unsupervised domain adaptation needs to take out the original source data and target data for use at the same time [2,6]. By dividing the right to own the data and the right to adjust the model, source-free UDA and federated learning provide the basis for privacy protection for diagnosis [7]. When the original source data is absolutely invisible, these algorithms use the information of the remaining parameters of the previously learned source model to dynamically and repeatedly adjust the device for reading target features through pseudo-label clustering. At the same time, using the mechanism of selecting the nearest center to filter, many noisy pseudo-tags are removed from the unlabeled data stream, thus reconstructing the space of hidden features and making the data distribution accurate. The diagram in Figure 3 shows the actual working mode of source-free adaptation under the privacy restriction between enterprises.

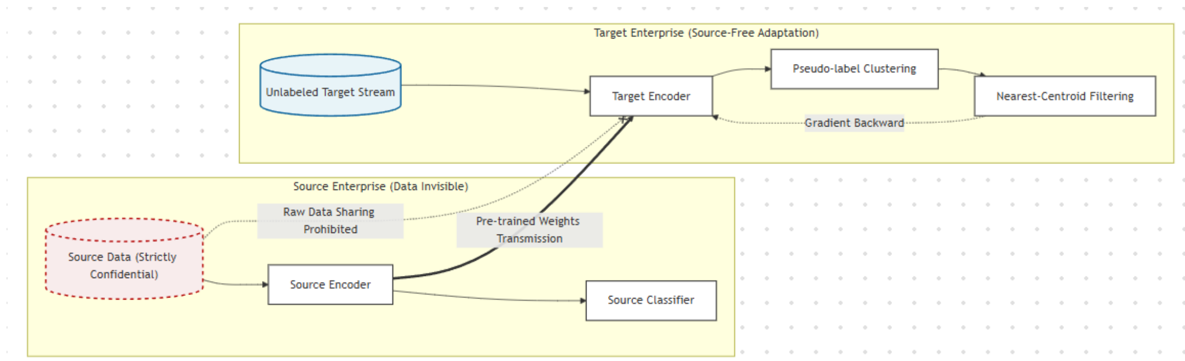

Figure 3. Source-free distributed architecture and feature reconstruction paradigm under cross-enterprise privacy isolation.

We want to eliminate the limitations of more single-plant source-free adaptation. Recently, a detailed survey [1] pointed out that everyone is trying to study generative self-tuning frameworks for generating source free feature alignment without looking at the original data. However, this generative approach is very dependent on the quality of the original pre-trained source model, and it is difficult to popularize it well in complex multi-plan cooperation networks. Ren and Li [7] distributed feature alignment processing without sharing the original data. They put forward IDD-LUDA-FL, which deeply combined Federated Learning (FL) and lightweight dynamic UDA, and created the ultimate privacy-preserving paradigm. This mechanism uses dynamic aggregation strategies to transfer diagnostic knowledge safely, and absolutely does not allow others to see local data. Therefore, the problem that the system cannot be well extended among enterprises is completely solved. But this source-free defense mechanism can protect the knowledge security between enterprises, but if you encounter very few sample stream at the beginning of the production of target plants, There is bound to be a great statistical deviation between centroid filtering and pseudo-label clustering, which directly leads to the physical constraint of extreme fault sample scarcity between cold-start phase.

2.3 Generative Compensation and Manifold Interpolation under Extremely Limited Sample Cold Starts

The cold-start phase of industrial machines includes the initial switching of production and operation states. At this point, the system will encounter a serious data imbalance problem anyway. Obviously, there are many ordinary driving data, but the samples of fault are completely few. Due to these physical conditions, the target fault feature space is very scattered and discontinuous. The common global distribution alignment algorithm can’t grasp the correct boundary between classes, so the problem of mode collapse will appear. For the physical discontinuity of this data distribution, generative feature compensation and manifold geometric reconstruction are the core solutions. First of all, using conditional diffusion models can fundamentally eliminate the feature distribution gaps with fewer fault types. Under the condition of no teacher, using the domain guidance mechanism and joint prior distribution, the sampling process is directed to the target domain through the classifier gradient, and the high-fidelity enhanced target sample is synthesized [9]. Basically, this process consists of a forward noise-adding Markov chain and a parameterized reverse denoising process. In the opposite phase, the model will be deeply guided to the cross-entropy gradients of a pre-trained source classifier. This clear gradient guide makes the noise absolutely mapped on the manifold of target domain, and the pseudo-fault samples are not meaningless Gaussian noise, but correct physical degradation semantics. Therefore, even if there is no real target fault samples at all, the boundary line of judgment can be well established. On the other hand, when working in the distribution of very few data point distributions, the technologies of Deep Transformation-Driven Subspace Interpolation and local manifold embedding depend on the source domain and target, which not only maintains the original geometric topology of the original feature space, but also gradually absorbs the domain offset [10, 14]. It enhances the good representation ability of the domain-invariant features under the restriction of small samples. Figure 4 shows the process of generative compensation and manifold geodesic, which can fill the physical gap caused by very few real target samples.

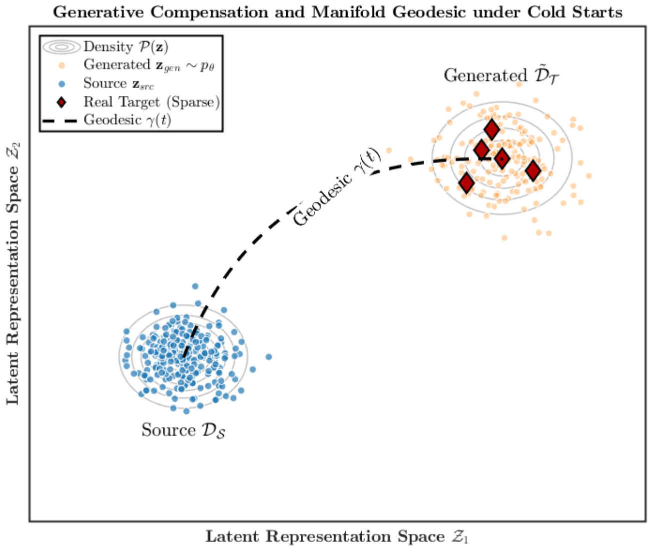

Figure 4. Generative compensation and manifold geodesic interpolation under extremely limited sample cold starts.

Having effectively dismantled the acute sample scarcity and cold-start dilemmas within single-source nodes, the multi-source heterogeneous data fusion conflicts and local feature shifts inherent to large-scale pipeline networks and complex machinery logically constitute the subsequent intricate engineering challenge demanding resolution by multidimensional domain adaptation technologies.

2.4 Adversarial Aggregation with Variance Counterbalancing under Multi-Source Heterogeneous Conflicts

In the wide-area monitoring of large units and complex pipe networks, the local data of the collected signals are very small because of the interleaving of multi-dimensional sensor networks, resulting in the characteristics of multi-source heterogeneity. Under this complex physical correspondence, ordinary single-source domain transmission and rough global distribution alignment will overlap different local feature spaces, leading to serious negative transmission phenomenon. For example, Zhu et al. [11] created a multi-view potential spatial learning framework for multi-source adaptation. This is consistent with the universal multi-source framework using teacher-free clustering [15]. However, due to the use of suspected tags under complex countermeasures, serious negative forwarding will still occur. To solve this heterogeneous conflict of multiple sources, we must abandon the single global recognition framework and set up our own independent cross-domain recognizer for each source domain. The distributed hostile training mechanism can deeply mine the cooperation information hidden between multi-source data and realize the global pre-aggregation of multi-source heterogeneous data in feature space [12]. However, if we only rely on global aggregation, the distinction between subtle local geometries in manifold will disappear. Therefore, in order to correct the deviation of local feature, gradient auxiliary machinery is used. By matching the exact gradient direction between similar examples, this method can well solve the feature confusion caused by local equipment [13]. At the same time, local manifold embedding technology can accurately adjust the feature changes of each domain and retrieve the invariant properties of features common to all domains. In this way, the clarity of local discriminant boundary can be maintained even when the information depth of multiple source is aligned [13]. Figure 5 lists the distributed adversarial aggregation network that use independent minimum aggregation to balance variance.

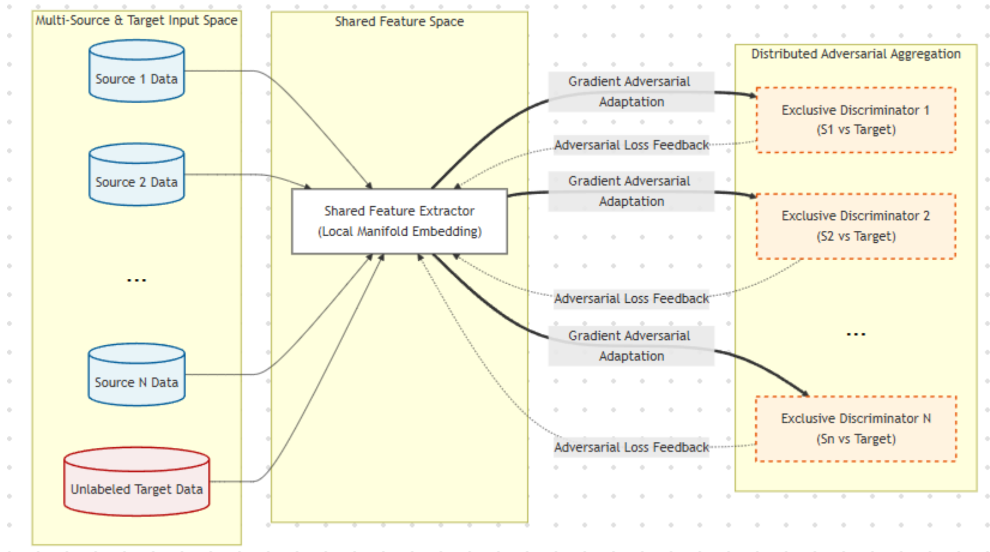

Figure 5. Distributed adversarial aggregation network configured with variance counterbalancing under multi-source heterogeneous conflicts.

We have completely solved the four physical limitations of time-varying evolution, privacy isolation, extreme small-sample cold starts and multi-source heterogeneity. The basic logic of unsupervised domain adaptation technology is profound and there is no contradiction. From the ideal laboratory model to the closed-loop technology widely used in the long tail scene of real industry, everything is done.

3. FUTURE EVOLUTIONARY TRAJECTORIES

3.1 Deep Integration of Physics-Informed Mechanisms

Unsupervised domain adaptation, which works entirely on data, has strong mapping ability and can eliminate all kinds of physical restrictions. However, the black-box method, which only relies on statistical alignment, is a very sparse long-tail in real industrial scenes, which requires a deep combination of data processes and physical mechanisms. It includes fully embedding known physical rules (such as motion equation of rotating machine, gear meshing frequency and resonance response) into neural network mechanism as regularization punishment or structural constraint. By optimizing the extracted machine physical information and the cross-domain deep feature space together, the physics-informed framework not only constructs reliable false labels in the unlabeled target domain, but also effectively constrains the hypothetical space in the alignment process [16]. The essence of this deep integration mechanism is to use objective physical laws to eliminate the naturally occurring spurious correlations in the global adversarial distribution alignment. In this way, even in extreme domain shifts, decision boundary can be kept in a completely unchanged hard state. With the development of this technology, the domain adaptation model fundamentally provides important engineering interpretability required by safety-critical domains. This is a paradigm for industrial intelligent diagnostics to change from simple data fitting to physics-informed “white-box mapping” of physical information.

3.2 Minimalist Architectural Descent Toward Edge Computing

The computational power of cloud can run very large mechanisms such as conditional diffusion models, but when it is used in actual factories, the network is often difficult to connect. In addition, the memory of edge nodes such as micro programmable logic controllers is very small, and the available power is fixed. The structure of cloud requires a lot of calculation, and edge devices must work for a very short time, so it is difficult to be widely used. If domain adaptation can’t be reasoned or dynamically adjusted on edge, the promise of being able to respond quickly in changing situations will become useless in the factory.

Aiming at this edge deployment problem, the relaxed Unsupervised Domain Adaptation Framework creates an easy way forward. By combining the minimum network background with parameter quality and conceptual technology depth, this structure provides model parameters and floating point operational overhead that are not needed in the feature mapping stage [7]. Specifically, in the quantization process, the high-precision floating point calculation is directly replaced by fast integer calculation, and the error of the answer is minimized by the lookup table calculated in advance. There is no need for an extra large and difficult teacher network. Under the strict physical limitation of edge's memory and power consumption, the combination of light structure design and low bit quantization mechanism can well protect the cross domain performance of high-level feature without degrading the quality. In addition, in the domain adversarial alignment, the compression of this structure will maintain the absolute rigidity of the decision boundary. Therefore, it can solve the technical problems when moving the model to the micro edge node as a whole.

3.3 Convergence with Digital Twins and Industrial Foundation Models

In addition to changing the structure of the algorithm, the biggest progress in unsupervised domain adaptation is to create a physical closed volume of macro data. Combining Digital Twin (DT) technology with Industrial Foundation Models (IFMs) is a new field with great potential. DTs can simulate many abnormal out-of-distribution (OOD) actions such as strong friction of rotor and aging at extreme high temperature. Then, you can make a lot of high-quality synthetic source data. At the same time, IFMs, which has been learned in advance by many industrial data such as vibration, acoustics and thermal imaging in exabyte, originally has a strong and widely used feature space. Using parameter-efficient fine-tuning (PEFT) technology, such as Low-Rank Adaptation (LoRA), the adaptive work of domain adaptation based on this large basic model has been learned from the beginning, and it has become only necessary to cooperate with the completed high-intelligence representation space. The change of this idea will completely eliminate the dependence on many actual target data. Then, domain adaptation is pushed to the direction that can be used in real zero-shot engineering.

4. CONCLUSION

This paper systematically checks the UDA implementation gap in the industrial diagnostics. Different from the simple arrangement of ordinary algorithms, we establish an orthogonal separation framework, and accurately apply the abstract alignment mechanism to four specific physical constraint. The fourth is time-varying evolution, privacy isolation, extreme cold starts and multi-source conflicts. Finally, to make domain adaptation truly technically available, three evolutions are needed. That is to combine physics-informed mechanism, lightweight edge computing and industrial basic model.

This paper has theoretical function, but this review has some shortcomings. First, there is no overall bibliometric analysis to express how the research papers of UDA develop statistically. Second, the orthogonal separation framework proposed this time is based on logical summary. In this study, the effect of end-to-end has not been directly confirmed in the experiment. Thirdly, some possible evolutionary paths-especially the systematic combination of Industrial Foundation Models and Digital Twins-are still in the initial stage of thinking and need to be confirmed by experiments in future research.

REFERENCES

[1] N. Zhang, J. Lu, K. Li, Z. Fang, and G. Zhang, "Source free unsupervised domain adaptation: Current research and future directions," Neurocomputing, vol. 564, p. 126921, 2024. DOI: 10.1016/j.neucom.2023.126921

[2] Y. Fang, P. T. Yap, W. Lin, H. Zhu, and M. Liu, "Source free unsupervised domain adaptation: A survey," Neural Networks, vol. 174, p. 106230, 2024. DOI: 10.1016/j.neunet.2024.106230

[3] C. Lin, Y. Kong, Q. Han, X. Zhang, J. Qi, M. Rao, and F. Chu, "An unsupervised multi level fusion domain adaptation method for transfer diagnosis under time varying working conditions," Mechanical Systems and Signal Processing, vol. 228, p. 112458, 2025. DOI: 10.1016/j.ymssp.2025.112458

[4] X. Wang, H. Jiang, M. Mu, and Y. Dong, "A dynamic collaborative adversarial domain adaptation network for unsupervised rotating machinery fault diagnosis," Reliability Engineering & System Safety, vol. 255, p. 110662, 2025. DOI: 10.1016/j.ress.2024.110662

[5] P. Lian, J. Zou, J. Tang, and S. Fan, "Continual unsupervised domain adaptation with structure preserving probabilistic anchors for rotating machinery fault diagnosis," Advanced Engineering Informatics, vol. 70, p. 104216, 2026. DOI: 10.1016/j.aei.2024.104216

[6] J. Wang, H. Zhang, and Q. Miao, "Source free unsupervised domain adaptation for electro mechanical actuator fault diagnosis," Chinese Journal of Aeronautics, vol. 36, no. 4, pp. 252 267, 2023. DOI: 10.1016/j.cja.2022.08.016

[7] C. Renfei and L. Zhongwen, "Industrial defect detection for data privacy and domain differences: Based on federated learning and unsupervised domain adaptation," Expert Systems with Applications, p. 131265, 2026. DOI: 10.1016/j.eswa.2023.122676

[8] R. Fang, K. Wang, J. Li, X. Yuan, and Y. Wang, “Unsupervised domain adversarial network for few sample fault detection in industrial processes,” Advanced Engineering Informatics, vol. 61, p. 102684, 2024. DOI: 10.1016/j.aei.2024.102684

[9] Y. Zhang, S. Chen, W. Jiang, Y. Zhang, J. Lu, and J. T. Kwok, “Domain guided conditional diffusion model for unsupervised domain adaptation,” Neural Networks, vol. 184, p. 107031, 2025. DOI: 10.1016/j.neunet.2024.107031

[10] K. Kumar, A. Majumdar, A. A. Kumar, and M. G. Chandra, “Unsupervised domain adaptation for machine fault diagnosis via subspace interpolation using deep transforms,” IEEE Sensors Journal, vol. 24, no. 13, pp. 20959 20969, 2024. DOI: 10.1109/JSEN.2024.3398364

[11] C. Zhu, Q. Wang, Y. Xie, and S. Xu, “Multiview latent space learning with progressively finetuned deep features for unsupervised domain adaptation,” Information Sciences, vol. 662, p. 120223, 2024. DOI: 10.1016/j.ins.2023.120223

[12] D. Xu, Y. Li, Y. Song, L. Jia, and Y. Liu, “IFDS: An intelligent fault diagnosis system with multisource unsupervised domain adaptation for different working conditions,” IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1 10, 2021. DOI: 10.1109/TIM.2020.3033423

[13] C. Wang, Z. Wang, H. Liu, H. Dong, and G. Lu, “An optimal unsupervised domain adaptation approach with applications to pipeline fault diagnosis: Balancing invariance and variance,” IEEE Transactions on Industrial Informatics, vol. 20, no. 8, pp. 10019 10030, 2024. DOI: 10.1109/TII.2024.3375836

[14] K. Kumar, A. Majumdar, A. A. Kumar, and M. G. Chandra, “Transform based subspace interpolation for unsupervised domain adaptation applied to machine inspection,” in Proc. 31st European Signal Processing Conference, pp. 1708 1712, IEEE, 2023. DOI: 10.23919/EUSIPCO58844.2023.10289871

[15] J. Tian, D. Han, H. R. Karimi, Y. Zhang, and P. Shi, “A universal multi source domain adaptation method with unsupervised clustering for mechanical fault diagnosis under incomplete data,” Neural Networks, vol. 173, p. 106167, 2024. DOI: 10.1016/j.neunet.2024.106167

[16] N. Jia, W. Huang, C. Ding, J. Wang, and Z. Zhu, “Physics informed unsupervised domain adaptation framework for cross machine bearing fault diagnosis,” Advanced Engineering Informatics, vol. 62, p. 102774, 2024. DOI: 10.1016/j.aei.2024.102774