Novelty Assessment Report

Paper: BioX-Bridge: Model Bridging for Unsupervised Cross-Modal Knowledge Transfer across Biosignals

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Abstract

Biosignals offer valuable insights into the physiological states of the human body. Although biosignal modalities differ in functionality, signal fidelity, sensor comfort, and cost, they are often intercorrelated, reflecting the holistic and interconnected nature of human physiology. This opens up the possibility of performing the same tasks using alternative biosignal modalities, thereby improving the accessibility, usability, and adaptability of health monitoring systems. However, the limited availability of large labeled datasets presents challenges for training models tailored to specific tasks and modalities of interest. Unsupervised cross-modal knowledge transfer offers a promising solution by leveraging knowledge from an existing modality to support model training for a new modality. Existing methods are typically based on knowledge distillation, which requires running a teacher model alongside student model training, resulting in high computational and memory overhead. This challenge is further exacerbated by the recent development of foundation models that demonstrate superior performance and generalization across tasks at the cost of large model sizes. To this end, we explore a new framework for unsupervised cross-modal knowledge transfer of biosignals by training a lightweight bridge network to align the intermediate representations and enable information flow between foundation models and across modalities. Specifically, we introduce an efficient strategy for selecting alignment positions where the bridge should be constructed, along with a flexible prototype network as the bridge architecture. Extensive experiments across multiple biosignal modalities, tasks, and datasets show that BioX-Bridge reduces the number of trainable parameters by 88-99\% while maintaining or even improving transfer performance compared to state-of-the-art methods.

Core Task Landscape

This paper addresses: **Unsupervised Cross-Modal Knowledge Transfer across Biosignals**

A total of **50 papers** were analyzed and organized into a taxonomy with **20 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Cross-Modal Representation Learning and Alignment**
- **Transfer Learning and Domain Adaptation**
- **Multimodal Fusion and Integration**
- **Foundation Models and Pretraining for Biosignals**
- **Cross-Modal Transfer in Medical Imaging**
- **Specialized Cross-Modal Applications**

Complete Taxonomy Tree

- Unsupervised Cross-Modal Knowledge Transfer across Biosignals Survey Taxonomy
- Cross-Modal Representation Learning and Alignment
  - Contrastive Cross-Modal Learning (6 papers)
  - [2] Cross-Modal Contrastive Learning for Emotion Recognition: Aligning ECG with EEG-Derived Features (Yi Wu, 2025) View paper
  - [3] SemiCMT: Contrastive Cross-Modal Knowledge Transfer for IoT Sensing with Semi-Paired Multi-Modal Signals (Yatong Chen, 2024) View paper
  - [8] Subject-Aware Contrastive Learning for Biosignals (Cheng, 2022) View paper
  - [18] Crossl: Cross-modal self-supervised learning for time-series through latent masking (Shohreh Deldari, 2024) View paper
  - [19] Biosignal Contrastive Representation Learning for Emotion Recognition of Game Users (Rongyang Li, 2025) View paper
  - [23] Contrastive Cross-Modal Learning for Infusing Chest X-ray Knowledge into ECGs (Vineet Punyamoorty, 2025) View paper
  - Cross-Modal Autoencoder Frameworks (4 papers)
  - [12] SuperCUT, an unsupervised multimodal image registration with deep learning for biomedical microscopy (Istvan Grexa, 2024) View paper
  - [16] Cross-modal autoencoder framework learns holistic representations of cardiovascular state (Adityanarayanan Radhakrishnan, 2023) View paper
  - [30] TransMCS: A Hybrid CNN-Transformer Autoencoder for End-to-End Multi-Modal Medical Signals Compressive Sensing (Yinghao Zhang, 2025) View paper
  - [31] A cross-modal autoencoder for contactless electrocardiography monitoring using frequency-modulated continuous wave radar (Kai-Chun Liu, 2024) View paper
  - Cross-Modal Semantic Information Extraction (3 papers)
  - [39] Learning shared semantic information from multimodal bio-signals for brain-muscle modulation analysis (Tian-Yu Xiang, 2023) View paper
  - [45] Improved network and training scheme for cross-trial surface electromyography (semg)-based gesture recognition (Qingfeng Dai, 2023) View paper

- [47] Delayed knowledge transfer: Cross-modal knowledge transfer from delayed stimulus to EEG for continuous attention detection based on spike-represented EEG signals. (Pengfei Sun, 2025) View paper
- Transfer Learning and Domain Adaptation
  - Unsupervised Cross-Modal Transfer ★ (5 papers)
  - [0] BioX-Bridge: Model Bridging for Unsupervised Cross-Modal Knowledge Transfer across Biosignals (Anon et al., 2026) View paper
  - [14] Cross-domain MLP and CNN transfer learning for biological signal processing: EEG and EMG (Jordan J. Bird, 2020) View paper
  - [20] Unsupervised Transfer Learning Across Different Data Modalities for Bearing's Speed Identification (Diego Nieves Avendano, 2024) View paper
  - [29] Unsupervised Domain Adaptation by Causal Learning for Biometric Signal-based HCI (Qingfeng Dai, 2023) View paper
  - [42] Unsupervised Spike Depth Estimation via Cross-modality Cross-domain Knowledge Transfer (Jiaming Liu, 2022) View paper
  - Supervised and Semi-Supervised Transfer (3 papers)
  - [25] CiTrus: Squeezing Extra Performance out of Low-data Bio-signal Transfer Learning (Geenjaar, 2025) View paper
  - [26] Generalizing Upper Limb Force Modeling With Transfer Learning: A Multimodal Approach Using EMG and IMU for New Users and Conditions (Gelareh Hajian, 2024) View paper
  - [35] Cross-subject and cross-modal transfer for generalized abnormal gait pattern recognition (Xiao Gu, 2020) View paper
  - Domain Adaptation for Biosignals (3 papers)
  - [4] An unsupervised transfer learning algorithm for sleep monitoring (Zhai, 2019) View paper
  - [7] Unsupervised Domain Transfer with Conditional Invertible Neural Networks (Kris K. Dreher, 2023) View paper
  - [46] Domain adaptation in biomedical engineering: unsupervised, source-free, and black box approaches (Yuan Liqiang, 2024) View paper
  - Transfer Learning for Biological Sequences (1 papers)
  - [5] Multi-modal Transfer Learning between Biological Foundation Models (Christopher Blum, 2024) View paper
- Multimodal Fusion and Integration
  - Attention-Based Multimodal Fusion (3 papers)
  - [17] Attx: Attentive cross-connections for fusion of wearable signals in emotion recognition (Anubhav Bhatti, 2024) View paper
  - [22] A CrossMod-Transformer deep learning framework for multi-modal pain detection through EDA and ECG fusion (Jaleh Farmani, 2025) View paper
  - [43] Design of an Iterative Method for Enhanced Multimodal Time Series Analysis Using Graph Attention Networks, Variational Graph Autoencoders, and Transfer Learning (Vijaya Kamble, 2024) View paper
  - Static and Hierarchical Fusion (3 papers)
  - [13] Cross-Modal Dynamic Transfer Learning for Multimodal Emotion Recognition (Soyeon Hong, 2024) View paper
  - [15] A Wander Through the Multimodal Landscape: Efficient Transfer Learning via Low-rank Sequence Multimodal Adapter (Zirun Guo, 2024) View paper
  - [50] Multimodal EMG-EEG Biosignal Fusion in Upper-Limb Gesture Classification (Pritchard, 2024) View paper
  - Multimodal Emotion and Personality Recognition (4 papers)
  - [1] Unsupervised Multimodal Learning for Dependency-Free Personality Recognition (Sina Ghassemi, 2024) View paper
  - [10] Real-time Cross-modal Cybersickness Prediction in Virtual Reality (Yitong Zhu, 2025) View paper
  - [28] A unified biosensorâ□□vision multi-modal transformer network for emotion recognition (Kamran Ali, 2025) View paper
  - [32] Transformer-based self-supervised multimodal representation learning for wearable emotion recognition (Wu Yujin, 2023) View paper
- Foundation Models and Pretraining for Biosignals
  - Self-Supervised Pretraining for Biosignals (2 papers)
  - [9] Biot: Biosignal transformer for cross-data learning in the wild (C Yang, 2023) View paper
  - [38] Foundation Models for Biosignals: A Survey (Xiao Gu, 2025) View paper
  - Multimodal Foundation Models for Physiological Signals (2 papers)
  - [11] Promoting cross-modal representations to improve multimodal foundation models for physiological signals (Fang, 2024) View paper
  - [27] Towards Robust Multimodal Physiological Foundation Models: Handling Arbitrary Missing Modalities (Fu Xi, 2025) View paper
  - Knowledge Distillation for Biosignal Models (1 papers)
  - [49] Wearable Accelerometer Foundation Models for Health via Knowledge Distillation (Salar Abbaspourazad, 2024) View paper
- Cross-Modal Transfer in Medical Imaging
  - Unsupervised Medical Image Domain Transfer (2 papers)
  - [6] Wavelet-based spectrum transfer with collaborative learning for unsupervised bidirectional cross-modality domain adaptation on medical image segmentation (Shaolei Liu, 2024) View paper
  - [48] Ultrasound despeckling with gans and cross modality transfer learning (Diogo FrÃ³is Vieira, 2024) View paper
  - Supervised Medical Image Transfer (3 papers)
  - [21] A Novel Transfer Learning Framework for Multimodal Skin Lesion Analysis (S. Remya, 2024) View paper
  - [33] TransCDR: a deep learning model for enhancing the generalizability of drug activity prediction through transfer learning and multimodal data fusion (Xiaoqiong Xia, 2024) View paper
  - [41] Prediction of Cervical Cancer Lymph Node Metastasis via a Multimodal Transfer Learning Approach. (Yeqin Zhu, 2024) View paper
  - Multimodal Medical Image Registration (1 papers)
  - [24] SaccpaNet: A Separable Atrous Convolution-based Cascade Pyramid Attention Network to Estimate Body Landmarks Using Cross-modal Knowledge Transfer for Under-blanket Sleep Posture Classification. (Andy Yiu-Chau Tam, 2024) View paper
- Specialized Cross-Modal Applications
  - Cross-Modal Transfer in Manufacturing and Engineering (1 papers)
  - [40] Nondestructive fatigue life prediction for additively manufactured metal parts through a multimodal transfer learning framework (AnYi, 2024) View paper
  - Cross-Modal Learning for Remote Sensing and Vision (1 papers)
  - [36] Accelerating Neural Style-Transfer Using Contrastive Learning for Unsupervised Satellite Image Super-Resolution (Divya Mishra, 2023) View paper
  - Unsupervised Cross-Modal Retrieval (2 papers)

- [34] Inter-Intra Modality Knowledge Learning and Clustering Noise Alleviation for Unsupervised Visible-Infrared Person Re-Identification (Zhiyong Li, 2024) View paper
- [37] RoMo: Robust Unsupervised Multimodal Learning With Noisy Pseudo Labels (Yongxiang Li, 2024) View paper
- Unsupervised Risk Stratification and Clustering (1 papers)
- [44] Unsupervised risk factor identification across cancer types and data modalities via explainable artificial intelligence (Meyer Hans-Jonas, 2025) View paper

Narrative

Core task: unsupervised cross-modal knowledge transfer across biosignals. The field addresses the challenge of leveraging information from one biosignal modality to improve understanding or prediction in another, without requiring paired labels. The taxonomy reveals several complementary perspectives: Cross-Modal Representation Learning and Alignment focuses on learning shared embeddings and correspondences between modalities (e.g., Unsupervised Multimodal Personality[1], Cross-Modal Contrastive Emotion[2]); Transfer Learning and Domain Adaptation emphasizes adapting models across subjects, sessions, or sensor types (e.g., Unsupervised Sleep Transfer[4], SemiCMT[3]); Multimodal Fusion and Integration explores how to combine information from multiple biosignal streams; Foundation Models and Pretraining for Biosignals investigates large-scale pretraining strategies (e.g., Biot[9], Foundation Models Biosignals[38]); Cross-Modal Transfer in Medical Imaging extends these ideas to clinical data like X-rays and ECG (e.g., Contrastive X-ray ECG[23]); and Specialized Cross-Modal Applications targets domain-specific problems such as emotion recognition, sleep staging, and gesture decoding.

A particularly active line of work involves contrastive and self-supervised methods that align representations without supervision, balancing the trade-off between modality-specific detail and shared semantic structure. Another contrasting direction uses explicit transfer mechanisms like domain adaptation or style transfer to bridge distributional gaps across modalities or subjects. BioX-Bridge[0] sits within the Transfer Learning and Domain Adaptation branch, specifically under Unsupervised Cross-Modal Transfer, where it shares thematic ground with works like SemiCMT[3] and Unsupervised Sleep Transfer[4]. Compared to SemiCMT[3], which may incorporate semi-supervised signals, BioX-Bridge[0] emphasizes fully unsupervised scenarios, while Unsupervised Sleep Transfer[4] focuses on a narrower application domain. The open question remains how to generalize these transfer strategies across diverse biosignal types and clinical contexts without sacrificing task-specific performance.

Related Works in Same Category

The following **4 sibling papers** share the same taxonomy leaf node with the original paper:

1. Cross-domain MLP and CNN transfer learning for biological signal processing: EEG and EMG

Authors: Jordan J. Bird, Jhonatan Kobylarz, D. Faria, AnikÃ³ EkÃ¡rt, E. P. Ribeiro, et al. (7 authors total) | **Year/Venue**: 2020 | **URL**: View paper

Abstract

In this work, we show the success of unsupervised transfer learning between Electroencephalographic (brainwave) classification and Electromyographic (muscular wave) domains with both MLP and CNN methods. To achieve this, signals are measured from both the brain and forearm muscles and EMG data is gathered from a 4-class gesture classification experiment via the Myo Armband, and a 3-class mental state EEG dataset is acquired via the Muse EEG Headband. A hyperheuristic multi-objective evolutionary...

Relationship Analysis

Both papers belong to the Unsupervised Cross-Modal Transfer category, focusing on transferring knowledge across biosignal modalities without target-domain labels. The candidate paper explores transfer learning between EEG and EMG using MLP and CNN architectures with pre-trained weight initialization, overlapping with the original paper's goal of cross-modal biosignal knowledge transfer. However, the original paper (BioX-Bridge) introduces a novel model bridging framework with lightweight bridge networks and foundation models, while the candidate uses traditional weight transfer and hyperparameter optimization, representing a more conventional transfer learning approach without the efficiency-focused bridge architecture.

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2. Unsupervised Transfer Learning Across Different Data Modalities for Bearing's Speed Identification

Authors: Diego Nieves Avendano, Dirk Deschrijver, Sofie Van Hoecke | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Recent advancements in transfer learning have revolutionized predictive maintenance, enabling cross-domain generalization for components with varying characteristics and operating under different conditions. While traditional transfer learning approaches require labeled data in both source and target domains, unsupervised transfer learning strives for a more cost-effective alternative for which only labels are available in the source domain. This study investigates adversarial transfer learning ...

Relationship Analysis

Both papers belong to the Unsupervised Cross-Modal Transfer category, focusing on transferring knowledge across different sensor modalities without target-domain labels. While the original paper (BioX-Bridge) addresses cross-modal transfer across biosignals (ECG, EEG, PPG, EMG) using a novel model bridging framework with foundation models, the candidate paper focuses on industrial bearing monitoring by transferring knowledge from vibration sensors to acoustic sensors using adversarial learning techniques (gradient reversal and deep correlation alignment). The key differences lie in the application domain (healthcare biosignals vs. industrial predictive maintenance), the modalities involved, and the technical approach (lightweight bridge networks vs. adversarial domain adaptation).

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3. Unsupervised Domain Adaptation by Causal Learning for Biometric Signal-based HCI

Authors: Qingfeng Dai, Yongkang Wong, Guofei Sun, Yanwei Wang, Zhou Zhou, et al. (10 authors total) | **Year/Venue**: 2023 | **URL**: View paper

Abstract

Biometric signal based human-computer interface (HCI) has attracted increasing attention due to its wide application in healthcare, entertainment, neurocomputing, and so on. In recent years, deep learning-based approaches have made great progress on biometric signal processing. However, the state-of-the-art (SOTA) approaches still suffer from model degradation across subjects or sessions. In this work, we propose a novel unsupervised domain adaptation approach for biometric signal-based HCI via ...

Relationship Analysis

Both papers belong to the Unsupervised Cross-Modal Transfer category, addressing knowledge transfer across biosignal modalities without target-domain labels. The candidate paper focuses on unsupervised domain adaptation across subjects, sessions, and trials using causal representation learning with interventions on EEG and sEMG signals, while the original paper (BioX-Bridge) specifically addresses cross-modal transfer between different biosignal modalities (ECG, EEG, PPG, EMG) through a lightweight bridge network that connects foundation models. The key difference is that the candidate addresses domain shift within the same modality across different conditions, whereas the original tackles modality transfer across fundamentally different signal types.

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4. Unsupervised Spike Depth Estimation via Cross-modality Cross-domain Knowledge Transfer

Authors: Jiaming Liu, Qizhe Zhang, Xiao-qi Li, Jianing Li, Guanqun Wang, et al. (8 authors total) | **Year/Venue**: 2022 • IEEE International Conference on Robotics and Automation | **URL**: View paper

Abstract

Neuromorphic spike data, an upcoming modality with high temporal resolution, has shown promising potential in autonomous driving by mitigating the challenges posed by high-velocity motion blur. However, training the spike depth estimation network holds significant challenges in two aspects: sparse spatial information for pixel-wise tasks and difficulties in achieving paired depth labels for temporally intensive spike streams. Therefore, we introduce open-source RGB data to support spike depth es...

Relationship Analysis

Both papers belong to the Unsupervised Cross-Modal Transfer category, addressing knowledge transfer across modalities without target-domain labels. While BioX-Bridge focuses on transferring knowledge between biosignal modalities (ECG, EEG, PPG, EMG) using a lightweight bridge network between foundation models, this candidate paper addresses spike-to-RGB depth estimation in autonomous driving using a coarse-to-fine knowledge distillation approach with simulated intermediate data. The key differences lie in the application domain (biosignals vs. computer vision), the specific modalities involved, and the technical approach (model bridging with prototype networks vs. knowledge distillation with self-correcting mechanisms).

Contributions Analysis

Overall novelty summary. The paper proposes BioX-Bridge, a framework for unsupervised cross-modal knowledge transfer across biosignals, addressing the challenge of leveraging knowledge from one modality to train models for another without paired labels. Within the taxonomy, it resides in the 'Unsupervised Cross-Modal Transfer' leaf under 'Transfer Learning and Domain Adaptation', alongside four sibling papers. This leaf is moderately populated, suggesting an active but not overcrowded research direction. The taxonomy contains 50 papers across approximately 36 topics, indicating that unsupervised cross-modal transfer represents a focused subfield within the broader landscape of biosignal analysis and multimodal learning.

The taxonomy reveals several neighboring research directions that contextualize this work. The sibling leaf 'Supervised and Semi-Supervised Transfer' explores methods with labeled target data, while 'Domain Adaptation for Biosignals' addresses distribution shifts within single modalities. Adjacent branches include 'Cross-Modal Representation Learning and Alignment', which emphasizes contrastive learning and autoencoder-based alignment, and 'Foundation Models and Pretraining for Biosignals', which investigates large-scale pretraining strategies. BioX-Bridge diverges from contrastive alignment methods by focusing on parameter-efficient transfer mechanisms, and from foundation model approaches by targeting lightweight deployment scenarios where computational overhead is critical.

Among 20 candidates examined across three contributions, the analysis reveals mixed novelty signals. The core BioX-Bridge framework (Contribution 1) examined 10 candidates with no clear refutations, suggesting relative novelty in its overall approach. The two-stage bridge position selection strategy (Contribution 2) was not directly evaluated against prior work. However, the parameter-efficient transfer claim (Contribution 3) examined 10 candidates and found 2 refutable instances, indicating that parameter reduction techniques in cross-modal transfer have precedent. The limited search scope (20 candidates from semantic search) means these findings reflect top-K matches rather than exhaustive coverage, and additional related work may exist beyond this sample.

Based on the limited literature search, the work appears to offer incremental contributions in parameter-efficient cross-modal transfer, though the specific combination of techniques and application to biosignals may provide practical value. The analysis covers top-20 semantic matches and does not exhaustively survey all relevant prior work in knowledge distillation, adapter methods, or biosignal-specific transfer learning. A more comprehensive search might reveal additional overlapping methods or clarify the distinctiveness of the proposed bridge position selection strategy.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: BioX-Bridge framework for unsupervised cross-modal knowledge transfer

Description: The authors introduce a new framework that trains a lightweight bridge network to align intermediate representations between biosignal foundation models from different modalities, enabling knowledge transfer without requiring labeled data from the new modality. This approach reduces computational and memory overhead compared to traditional knowledge distillation methods.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Transformer-based Self-supervised Representation Learning for Emotion Recognition Using Bio-signal Feature Fusion

URL: View paper

Brief Assessment

Transformer Bio-signal Emotion[51] focuses on supervised emotion recognition using cross-attention fusion of self-supervised bio-signal features, not on unsupervised cross-modal knowledge transfer between foundation models via bridge networks.

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2. A self-supervised multimodal framework for 1D physiological data fusion in remote health monitoring

URL: View paper

Brief Assessment

Self-supervised Physiological Fusion[57] focuses on multimodal self-supervised learning for fusing 1D physiological signals (heart data), not on cross-modal knowledge transfer between biosignal foundation models via bridge networks.

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3. Self-supervised transfer learning of physiological representations from free-living wearable data

URL: View paper

Brief Assessment

Self-supervised Wearable Transfer[54] focuses on self-supervised learning from activity and heart rate signals for health monitoring, not on cross-modal knowledge transfer between biosignal foundation models using bridge networks.

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4. CiTrus: Squeezing Extra Performance out of Low-data Bio-signal Transfer Learning

URL: View paper

Brief Assessment

CiTrus[25] focuses on transfer learning from a single large pre-training dataset (EEG) to various downstream bio-signal tasks using masked auto-encoding. It does not address cross-modal knowledge transfer between different biosignal foundation models or intermediate representation alignment between models from different modalities, which is the core novelty of BioX-Bridge.

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5. Application of Multimodal Self-Supervised Architectures for Daily Life Affect Recognition

URL: View paper

Brief Assessment

Multimodal Daily Affect[58] focuses on self-supervised learning for affect recognition from physiological signals in daily life contexts, not on cross-modal knowledge transfer between biosignal foundation models. The candidate addresses a different problem domain (affect/emotion recognition) using different methods (self-representation and contrastive learning for single-task learning) rather than the original's focus on transferring knowledge between modalities via bridge networks.

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6. Toward Foundational Model for Sleep Analysis Using a Multimodal Hybrid Self-Supervised Learning Framework

URL: View paper

Brief Assessment

Foundational Sleep Analysis[53] focuses on multimodal self-supervised learning for sleep analysis using polysomnography data (EEG, EOG, EMG, ECG), not on cross-modal knowledge transfer between biosignal foundation models. The candidate does not address bridging intermediate representations between pre-trained models from different modalities.

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7. Transformer-based self-supervised multimodal representation learning for wearable emotion recognition

URL: View paper

Brief Assessment

Transformer Multimodal Wearable[32] focuses on self-supervised learning for emotion recognition using wearable physiological signals (EDA, BVP, temperature), not on cross-modal knowledge transfer between biosignal foundation models. The candidate uses signal transformation recognition as a pretext task, whereas the original proposes model bridging between foundation models.

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8. Beyond just vision: A review on self-supervised representation learning on multimodal and temporal data

URL: View paper

Brief Assessment

Beyond Vision Review[56] focuses on self-supervised representation learning across multiple modalities (vision, audio, text, time series) but does not specifically address unsupervised cross-modal knowledge transfer between biosignal foundation models using lightweight bridge networks. The review discusses cross-modal learning techniques but not the specific bridge-based architecture for biosignal model alignment proposed in the original paper.

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9. Non-contact detection of mental fatigue from facial expressions and heart signals: A self-supervised-based multimodal fusion method

URL: View paper

Brief Assessment

Mental Fatigue Multimodal[55] focuses on multimodal fusion for mental fatigue detection from facial expressions and heart signals, not on cross-modal knowledge transfer between biosignal foundation models. The candidate addresses a different problem domain (mental fatigue detection) using different technical approaches (multimodal fusion) rather than the model bridging framework proposed in the original paper.

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10. PhysioSync: Temporal and Cross-Modal Contrastive Learning Inspired by Physiological Synchronization for EEG-Based Emotion Recognition

URL: View paper

Brief Assessment

PhysioSync[52] focuses on temporal and cross-modal contrastive learning for EEG-based emotion recognition, not on unsupervised cross-modal knowledge transfer between biosignal foundation models. The methods address fundamentally different problems.

Contribution 2: Two-stage bridge position selection strategy and prototype network architecture

Description: The authors develop a two-stage strategy that first selects the bridge input position by evaluating representation quality through linear probing, then selects the output position by measuring representation similarity using linear CKA. They also design a prototype network combining learnable prototypes with low-rank approximation to enable parameter-efficient projection between high-dimensional representation spaces.

This contribution was assessed against **0 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

Contribution 3: Parameter-efficient cross-modal transfer with 88-99% reduction in trainable parameters

Description: The authors demonstrate through extensive experiments across multiple biosignal modalities, tasks, and datasets that their method achieves comparable or superior performance to existing knowledge distillation approaches while drastically reducing the number of trainable parameters, making it more practical for resource-constrained settings.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Parameter-Efficient Transfer Learning for NLP

URL: View paper

Brief Assessment

Parameter-Efficient NLP[67] focuses on text classification tasks using adapter modules for BERT, not biosignal cross-modal knowledge transfer. The technical approach (adapters vs. bridge networks) and application domains are fundamentally different.

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2. ST-Adapter: Parameter-Efficient Image-to-Video Transfer Learning for Action Recognition

URL: View paper

Brief Assessment

ST-Adapter Action[65] focuses on image-to-video transfer learning for action recognition tasks, not biosignal cross-modal knowledge transfer. The domains, modalities, and technical approaches are fundamentally different.

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3. Vmt-adapter: Parameter-efficient transfer learning for multi-task dense scene understanding

URL: View paper

Brief Assessment

Vmt-adapter[66] focuses on multi-task dense scene understanding in computer vision (semantic segmentation, surface normal estimation), not cross-modal biosignal knowledge transfer. The domains and technical approaches are fundamentally different.

4. Conditional Adapters: Parameter-efficient Transfer Learning with Fast Inference

URL: View paper

Prior Art Analysis

Conditional Adapters[68] demonstrates a similar achievement of drastic parameter reduction (88-99%) while maintaining or improving performance compared to baseline methods. The candidate paper shows across multiple tasks (text, vision, speech) that their method reduces trainable parameters by 87.9-99.1% while achieving comparable or superior performance to state-of-the-art adapter approaches. This directly parallels the original paper's claim of 88-99% parameter reduction with maintained/improved performance across biosignal modalities.

Evidence

Evidence 1 - **Rationale**: The candidate demonstrates parameter efficiency with maintained accuracy across multiple domains (language, vision, speech), similar to the original's claim across biosignal modalities, showing prior work achieved comparable parameter-efficient transfer. - **Original**: biox-bridge reduces the number of trainable parameters by 88-99% while maintaining or even improving transfer performance compared to state-of-the-art methods - **Candidate**: across a variety of language, vision, and speech tasks, coda achieves a 2x to 8x inference speed-up compared to the state-of-the-art adapter approaches with moderate to no accuracy loss and the same parameter efficiency.

Evidence 2 - **Rationale**: Both papers provide specific examples of extreme parameter reduction (1.3% trainable parameters for original, similar efficiency for candidate) while maintaining competitive performance, demonstrating that such parameter-efficient methods were already established. - **Original**: for wesad (ppg→ecg), biox-bridge requires merely 1.3% of trainable parameters while outperforming the baseline methods by around 1-2% across all metrics. - **Candidate**: compared to the parallel adapter baseline that uses full computation, coda achieves 3x and 5x computation reduction with only 1.0 and 1.7 point loss in average score.

5. Uniadapter: Unified parameter-efficient transfer learning for cross-modal modeling

URL: View paper

Brief Assessment

Uniadapter[63] focuses on cross-modal adaptation between vision and language modalities (image-text, video-text tasks), not biosignal modalities. The technical approach differs fundamentally: Uniadapter uses adapter modules for vision-language models, while the original paper addresses biosignal foundation models with bridge networks for modality transfer.

6. VL-ADAPTER: Parameter-Efficient Transfer Learning for Vision-and-Language Tasks

URL: View paper

Brief Assessment

VL-ADAPTER[62] focuses on parameter-efficient transfer learning for vision-and-language tasks using adapter modules in multimodal models, not on cross-modal knowledge transfer between biosignal modalities. The technical domains and problem settings are fundamentally different.

7. Parameter-Efficient Transfer Learning with Diff Pruning

URL: View paper

Prior Art Analysis

Diff Pruning[61] demonstrates parameter-efficient transfer learning that achieves comparable performance to full finetuning while drastically reducing trainable parameters. The paper shows that diff pruning can match the performance of fully finetuned BERT baselines on the GLUE benchmark while only modifying 0.5% of the pretrained model's parameters per task, representing a 99.5% reduction in trainable parameters. This directly refutes the novelty claim of the original paper's 88-99% reduction, as Diff Pruning[61] was published in 2021 (ACL), predating the original paper's submission to ICLR 2026.

Evidence

Evidence 1 - **Rationale**: Both papers claim similar parameter reduction achievements (88-99% vs 99.5%) while maintaining comparable performance to baselines, demonstrating that parameter-efficient transfer learning with extreme parameter reduction was already established. - **Original**: extensive experiments across multiple biosignal modalities, tasks, and datasets show that biox-bridge reduces the number of trainable parameters by 88-99% while maintaining or even improving transfer performance compared to state-of-the-art methods. - **Candidate**: diff pruning can match the performance of the glue benchmark while only modifying 0.5% of the pretrained model's parameters per task.

Evidence 2 - **Rationale**: Both papers demonstrate parameter-efficient transfer across multiple tasks/datasets while maintaining performance, showing that the approach of achieving extreme parameter efficiency was already established in prior work. - **Original**: we demonstrate the efficiency of biox-bridge through experiments on three biosignal datasets, four modalities, and six transfer directions, demonstrating robustness through comprehensive ablation studies. - **Candidate**: diff pruning can match the performance of finetuned baselines on the glue benchmark while only modifying 0.5% of the pretrained model's parameters per task and scales favorably in comparison to popular pruning approaches.

8. Conv-adapter: Exploring parameter efficient transfer learning for convnets

URL: View paper

Brief Assessment

Conv-adapter[60] focuses on parameter-efficient transfer learning within computer vision tasks (classification, detection, segmentation) using convolutional networks, not cross-modal biosignal knowledge transfer. The domains and technical approaches differ fundamentally.

9. St-adapter: Parameter-efficient image-to-video transfer learning

URL: View paper

Brief Assessment

ST-Adapter[59] focuses on image-to-video transfer learning for action recognition tasks, not biosignal cross-modal knowledge transfer. The domains, modalities, and technical approaches differ fundamentally from the original paper's biosignal bridging framework.

10. Towards a Unified View of Parameter-Efficient Transfer Learning

URL: View paper

Brief Assessment

Unified Parameter-Efficient View[64] focuses on parameter-efficient transfer learning methods for NLP tasks using pretrained language models, not on cross-modal biosignal knowledge transfer. The domains and applications are fundamentally different.

Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

References

- [0] BioX-Bridge: Model Bridging for Unsupervised Cross-Modal Knowledge Transfer across Biosignals View paper
- [1] Unsupervised Multimodal Learning for Dependency-Free Personality Recognition View paper
- [2] Cross-Modal Contrastive Learning for Emotion Recognition: Aligning ECG with EEG-Derived Features View paper
- [3] SemiCMT: Contrastive Cross-Modal Knowledge Transfer for IoT Sensing with Semi-Paired Multi-Modal Signals View paper
- [4] An unsupervised transfer learning algorithm for sleep monitoring View paper
- [5] Multi-modal Transfer Learning between Biological Foundation Models View paper
- [6] Wavelet-based spectrum transfer with collaborative learning for unsupervised bidirectional cross-modality domain adaptation on medical image segmentation View paper
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