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Self-Supervised Learning of ECG and PPG Signals for Multi-Modal Health Monitoring

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Abstract

Self-supervised multimodal time-series analysis faces critical challenges including cross-domain temporal shifts, sensor noise, and inter-subject variability, which degrade disease classification performance. Existing methods often depend on labeled data or explicit target domain alignment, limiting their clinical practicality. We propose TSTA-Net, a novel framework that integrates: (1) a residual spatiotemporal transformer (STN) to dynamically correct sensor shifts and motion artifacts, (2) a dual-branch Transformer for capturing long-range dependencies, and (3) hierarchical contrastive learning for spatiotemporal alignment of ECG and PPG signals. This integrated approach addresses both temporal dynamics and spatial inconsistencies through joint optimization. On atrial fibrillation detection, TSTA-Net achieves a 9.3% higher F1-score than state-of-the-art self-supervised methods, with ablation studies verifying that the spatiotemporal alignment mechanism contributes 68% of the performance gain. The lightweight framework ($<$1M parameters) reduces annotation dependency while enabling real-time arrhythmia screening on wearable devices, advancing self-supervised learning for practical healthcare applications.

Keywords: Multimodal, self-supervised Learning, Contrastive Learning, Temporal Physiological Signals

1. Introduction

Electrocardiogram (ECG) and photoplethysmogram (PPG) signals are indispensable tools for cardiovascular health monitoring, widely employed in arrhythmia detection and blood pressure management. (Liu et al., 2021) The ubiquity of wearable devices has enabled continuous acquisition of multimodal physiological time-series data, yet their clinical utility remains constrained by the high cost of expert annotations and regulatory barriers. Self-supervised learning emerges as a viable solution to mitigate reliance on labelled data by learning from raw signal patterns. (Krishnan et al., 2022) Despite the success of vision-language models like CLIP in static data alignment, their application to dynamic physiological signals is hindered by two fundamental challenges: (1) heterogeneous spatiotemporal characteristics between ECG and PPG, such as divergent sampling rates and noise profiles, which complicate cross-modal alignment; (2) inadequate modelling of long-range temporal dependencies critical for episodic conditions like atrial fibrillation, as existing methods predominantly depend on supervised learning with limited generalisation.

To address these challenges, we propose TSTA-Net (Time-Spatial Transformer Alignment Network), a self-supervised framework that unifies spatiotemporal alignment and temporal dependency learning for ECG-PPG signals. TSTA-Net incorporates a residual spatiotemporal transformer (STN) to dynamically rectify sensor misalignments, a dual-branch Transformer encoder to model both local rhythm irregularities and global waveform trends, and a hierarchical contrastive learning strategy to synchronise multimodal representations. By jointly optimising these components, the framework achieves robust feature extraction without manual annotations.

The contributions of this work are threefold.

We propose the first self-supervised framework integrating spatiotemporal alignment and long-term dependency modelling for ECG-PPG signals.

We design a lightweight architecture combining residual STN and dual-branch Transformers, achieving high accuracy with minimal parameters.

Extensive experiments demonstrate superior performance and generalisation across clinical and activity recognition tasks.

This advancement bridges self-supervised learning with wearable healthcare, enabling real-time, low-cost arrhythmia screening.

2. Related work

Developments in the field of multimodal representation learning have provided an important methodological foundation for dealing with the problem of modal heterogeneity. the CLIP model (Radford et al., 2021) achieved a breakthrough in cross-modal alignment of graphs and texts through contrast learning, and its "modality agnostic" projection head design provided key insights for physiological signals research. the dynamic dictionary and momentum updating mechanism proposed by the MoCo series (He et al., 2020) effectively solved the negative sample limitations of the small batch training. limitations, and its memory bank strategy has been migrated to physiological signal comparison tasks (Żygierewicz et al., 2022). Medical-specific models such as MedCLIP (Wang et al., 2022) significantly improve the efficiency of medical data utilisation by decoupling the contrast learning between medical images and clinical texts and combining domain knowledge to construct semantic matching loss. These works validate the universality of contrast learning in heterogeneous modal alignment, but the existing frameworks are mostly designed for static data such as images and texts, which is difficult to be directly applicable to dynamic time-series signals such as ECG/PPG.

In the field of physiological signal timing modelling, researchers have gradually constructed an adapted dynamic representation system. The Transformer-based ECG diagnostic model (Ribeiro et al., 2020) employs a hierarchical pre-training strategy, combining a global attention mechanism with a local feature extractor, to validate the clinical value of time-series modelling in arrhythmia detection.The TF-C method (Zhang et al., 2022) pioneers the introduction of contrast learning into ECG analysis, and achieves self-supervised feature extraction via time-frequency cross-modal comparisons, revealing its advantages in temporal discriminative learning. Additionally, the PhysioNet 2021 Challenge (van der Oord et al., 2018) highlighted hybrid CNN-Transformer architectures for ECG classification, while CPC (Grill et al., 2020) leveraged autoregressive modeling to capture future context in time series. However, the existing methods often neglect the domain offset problem caused by sensor bias and individual differences, resulting in degradation of the generalisation performance when deployed in practice. Despite significant progress in research on multimodal physiological signal characterisation based on self-supervised learning, a number of challenges remain.

The high cost of physiological signal data annotation, inter-modal data imbalance, and individual differences (Bota et al., 2019) limit the generalisation ability of the models. Especially in the case of data scarcity, the effectiveness of existing methods is often limited. To cope with these challenges, future research may focus on methods such as small sample learning, self-supervised learning, and cross-individual transfer learning, so as to effectively address the difficulties posed by data scarcity. Meanwhile, combining domain knowledge and interpretable AI techniques to further improve the practicality and reliability of models is also an important development direction.

In this context, this study focuses on the application of contrast learning in the time series (Yang et al., 2023), aiming to explore how to achieve efficient pre-training by constructing the intrinsic correlation between ECG and PPG signals. This method not only provides new perspectives for the pre-training of time series, but also provides new directions and challenges for future research. Improving the performance of the model in physiological signal analysis by combining the time-frequency joint comparison mechanism of ECG and PPG signals will be a key path to break through the bottleneck of the existing technology.

3. Method

To effectively capture complex temporal dependencies and align representations from multiple physiological signal modalities, we propose a novel multimodal contrastive learning model named TSTA-Net (Temporal-Spatial Transformer with Alignment Network). The architecture comprises four key components: a multi-strategy data augmentation module, dual-branch temporal encoders for ECG and PPG signals, a Spatial Transformation Network (STN), and a projection head optimized by both intra-modal and cross-modal contrastive objectives. This design enhances the model's ability to learn modality-invariant and discriminative features, enabling better performance on downstream tasks such as arrhythmia or activity classification. The overall framework is illustrated in Figure 1.

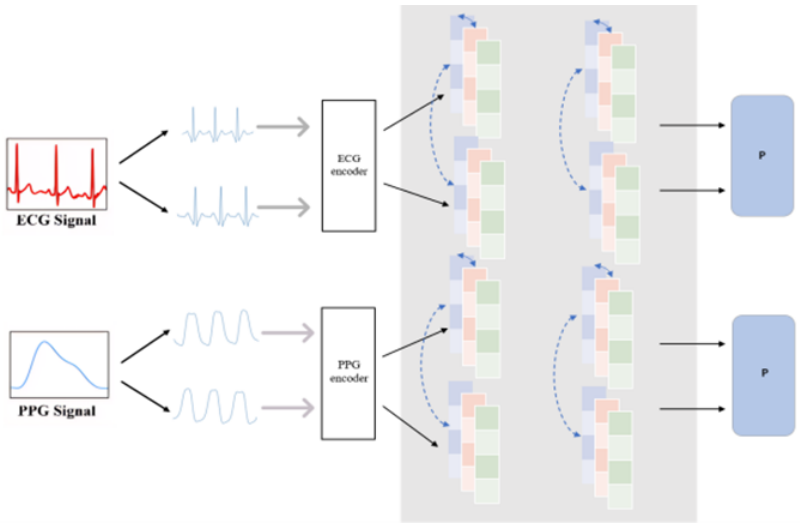

Figure 1: Architecture diagram of TSTA Net model

3.1. Feature Extraction Module

To improve model robustness and enhance data diversity, we apply stochastic signal augmentations including jittering, scaling, shifting, and Gaussian noise to the raw ECG and PPG inputs. During training, each signal is transformed into two views—original and augmented—providing the foundation for contrastive learning. These signals are then passed through modality-specific temporal encoders.

Each encoder consists of several 1D convolution layers followed by a Transformer encoder. The convolution layers capture local temporal features and reduce input length, while the Transformer utilizes self-attention to model long-range dependencies. This structure enables the model to focus on salient temporal patterns such as waveform shapes and rhythm changes.

To reduce the semantic gap between modalities, we introduce a Spatial Transformation Network (STN) that learns an optimal transformation to align the feature spaces of ECG and PPG. This transformation helps eliminate structural mismatches caused by differences in signal morphology. The aligned representations are further projected into a common embedding space using a cross-modal projection head, preparing the model for contrastive training.

3.2. Contrastive Loss Design

We design a joint contrastive loss that consists of intra-modal and cross-modal components. The intra-modal loss pulls together representations of a signal and its augmented view while pushing apart representations of different signals. It is defined as:

$$\mathcal{L}_{\text{intra}} = -\log \frac{\exp\left(\sin\left(z_i, z_i^+\right)/\tau\right)}{\sum_{k=1}^{2N} 1_{[k\neq i]} \exp\left(\sin\left(z_i, z_k\right)/\tau\right)} \tag{1}$$

where z_i and z_i^+ are representations of a signal and its augmentation, $\text{sim}(\cdot)$ denotes cosine similarity, and τ is the temperature parameter.

The cross-modal loss aligns ECG and PPG representations from the same instance. For each ECG feature z_i^{ECG}, its corresponding PPG feature z_i^{PPG} is the positive pair, while other PPGs in the batch are negatives:

$$\mathcal{L}_{\text{cross}} = -\log \frac{\exp\left(\frac{\sin\left(z_i^{ECG}, z_i^{PPG}\right)}{\tau}\right)}{\sum_{k=1}^{N} \exp\left(\frac{\sin\left(z_i^{ECG}, z_k^{PPG}\right)}{\tau}\right)} \tag{2}$$

The total loss combines the two with weights λ_1 and λ_2:

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{intra} + \lambda_2 \mathcal{L}_{cross} \tag{3}$$

This contrastive framework ensures intra-modal robustness and cross-modal alignment, which is essential for effective multimodal representation learning.

4. Experimental setup

4.1. Datasets and Implementation

This study employs three public datasets:

(1) MIMIC-III, comprising synchronized ECG and PPG signals (125 Hz) from over 40,000 ICU patients. 30-second segments were downsampled to 42 Hz. The AF classification task used subject-independent splits, with 1.2 million AF and 1.8 million Non-AF segments for training and validation.

(2) PPG-DaLiA, featuring PPG (64 Hz) and ECG (32 Hz) signals from 15 subjects during daily activities. The data was segmented into 8-second windows (PPG: 512, ECG: 256) and labeled for binary classification (sedentary vs. exercise).

(3) PTT Dataset, collected from 22 healthy subjects under three activity states (sit, walk, run). Signals (500 Hz) were segmented into 8-second windows (4,000 points) for a 3-class classification task. All datasets were anonymized and ethically reviewed.

4.2. Implementation Details

Datasets were split by subject ID to ensure generalization. Experiments were repeated 5 times, reporting mean $\pm$ std. The model was trained using Adam optimizer ($lr = 1e-4$, weight decay=0.35) for 60 epochs. Batch size was 16 (or 2 for small datasets). Data augmentations included time/frequency masking and random scaling. Key settings: Transformer depth=2, heads=2, hidden size=128, dropout=0.35; contrastive loss temperature τ=0.1; intra-modal loss weights λ_1=1, λ_2=0.8. Training was conducted on PyTorch 1.9 with RTX 3090 Ti GPUs.

4.3. Evaluation Metrics

Four metrics—Accuracy, Precision, Recall, and F1 score—were used. While accuracy reflects overall performance, F1 score better captures robustness under class imbalance, particularly for early AF detection. These indicators jointly evaluate model reliability and semantic alignment in multimodal representation learning. Experimental results across all three datasets validate the proposed model's effectiveness and generalizability in self-supervised temporal signal classification tasks.

5. Experiments Results

5.1. Comparison with Other Methods

To objectively evaluate the classification performance of our method, we compare it with several leading methods in time-series signal classification and self-supervised learning. All methods use ECG and PPG as input modalities and are tested under the same preprocessing conditions. The evaluation metrics include accuracy, precision, recall, F1 score, and Accuracy to Criterion (ACC). The results shown in Table 1 indicate that our method outperforms the others across all metrics. For instance, the F1 score of our approach reaches 89.83%, which is 2.01% higher than the second-best method, demonstrating the superior performance of our self-supervised multimodal contrastive learning strategy in capturing temporal feature correlations and modality relationships. The ROC and PR curves in Figure 2 further validate the robustness of our framework under class imbalance.

5.2. Ablation Experiments

Ablation experiments were conducted to verify the contribution of each module, such as the Spatial Transformation Network (STN), Contrast Loss, and Transformer Encoder. By removing each mod-

Table 1: Comparison with Existing Methods

Methodologies	Dataset	Pre(%)	Acc(%)	Recall(%)	F1 Score (%)
LSTM	MIMIC	65.61	66.47	64.20	64.92
BiLSTM	MIMIC	67.22	68.03	66.51	66.80
CLIP	MIMIC	82.51	83.10	82.00	82.06
TS-TCC	MIMIC	88.00	88.86	91.50	87.82
BYOL	MIMIC	81.20	82.05	83.11	82.57
SimCLR	MIMIC	76.43	75.55	72.10	72.84
TSTA-Net	MIMIC	91.27	90.80	90.25	89.83

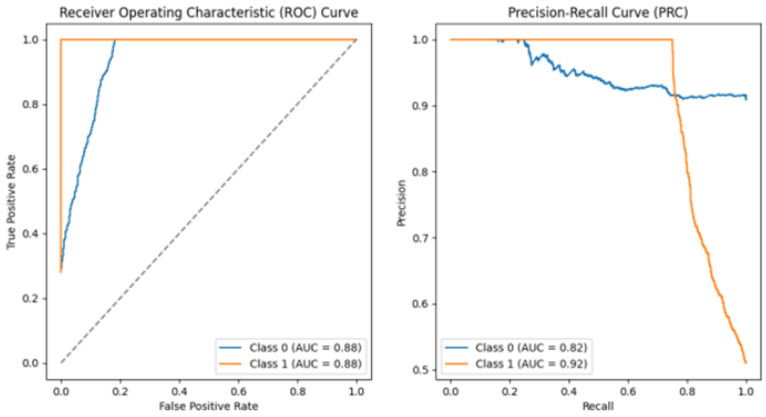

Figure 2: ROC and PRC Curves

ule, we observed the impact on model performance. Table 2 shows the results of these experiments on the MIMIC dataset.

Table 2: Ablation Experiments

Methodologies	Dataset	Accuracy (%)	F1 Score (%)	ACC (%)
Single ECG Mode	MIMIC	79.10	78.90	78.99
Single PPG Mode	MIMIC	76.30	75.21	77.70
Remove STN	MIMIC	85.73	82.50	83.10
Remove Contrast Loss	MIMIC	82.17	81.10	80.40
Remove Transformer Encoder	MIMIC	77.32	76.58	77.02
Full Model	MIMIC	91.27	89.83	90.25

The performance of single ECG and PPG modes was significantly lower, with F1 scores of 78.90% and 75.21%, respectively. This highlights the limitations of unimodal signals in detecting atrial fibrillation (AF), especially due to noise. Multimodal fusion notably enhanced performance, validating the complementary nature of the signals. Removing the STN module led to a 7.33% decrease in the F1 score, while the absence of contrast loss reduced it by 8.73%. The removal of the Transformer Encoder caused the largest drop, 13.25%, emphasizing its role in modeling

temporal dependencies. Ultimately, the full model achieved an F1 score of 89.83%, demonstrating the significance of all modules in spatiotemporal alignment, cross-modal learning, and temporal feature modeling.

5.3. Generalizability Experiments

To further assess the generalizability of our method, we tested it on two additional datasets: PPG-DaLiA and Pulse Transit Time (PTT). The PPG-DaLiA dataset, involving nine types of physical activities (e.g., sitting, walking, running), presents challenges due to individual differences and diverse acquisition environments. Our method achieved an F1 score of 76.35% and accuracy of 78.52%, outperforming other methods like TS-TCC (F1 = 72.18%) and SimCLR (Chen et al., 2020) (F1 = 65.73%). This result demonstrates the effectiveness of our approach in diverse environments, although the performance in the nine-class task was limited by the dataset's complexity and label distribution (see Table 3 for detailed metrics). Notably, CLIP, a vision-language model adapted to physiological signals, achieves only 68.19% F1, highlighting the challenge of directly migrating static-data methods to dynamic time-series analysis.

Table 3: Performance on Nine Classification Tasks (PPG-DaLiA)

Methodologies	Accuracy (%)	F1 Score (%)	Recall (%)	ACC (%)
TSTA-Net	78.52	76.35	77.84	80.28
TS-TCC	74.25	72.18	73.57	75.62
CLIP	70.48	68.19	69.76	71.98
SimCLR	68.41	65.73	66.92	70.31

In the PTT dataset, which involves a simpler three-class task (walking, running, sitting), our method achieved an F1 score of 90.25%, significantly outperforming TS-TCC (F1 = 86.58%) and SimCLR (F1 = 81.15%)(Table 4). This illustrates that clearer and more centrally labeled datasets improve performance. However, in more complex tasks with increased categories and data imbalance, performance may still be affected.

Table 4: Performance on Three-Class Classification (PTT)

Methodologies	Accuracy (%)	F1 Score (%)	Recall (%)	ROC-AUC (%)
TSTA-Net	90.84	90.25	90.50	91.72
TS-TCC	87.37	86.58	86.89	89.55
CLIP	85.48	80.25	83.54	86.98
SimCLR	82.62	81.15	81.94	88.21

6. Conclusions

We present TSTA-Net, a novel self-supervised representation learning framework for multimodal spatiotemporal alignment of ECG and PPG signals. The model enhances raw signals to create diverse views and employs a spatial-temporal transformer (STN) to correct sensor misalignments and reduce motion artifacts. A two-branch Transformer encoder captures long-range dependencies, while a hierarchical contrastive learning strategy enforces both intra-modal consistency and

cross-modal alignment. TSTA-Net achieves superior performance in AF detection and activity recognition, showing strong robustness in low-label and cross-domain scenarios. Its lightweight architecture supports real-time deployment on wearable devices, offering a promising solution for self-supervised medical time-series analysis and enabling low-cost, personalized health monitoring.

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