STAN: Spectral-Temporal Attention Networks for Multivariate Time-Series Anomaly Detection

Anonymous Author(s)
Affiliation
anonymous@email.com

Abstract

We introduce STAN (Spectral-Temporal Attention Networks), a dual-branch architecture that detects anomalies in multivariate time series by jointly modeling frequency-domain and temporal-domain representations. Existing methods process time series in a single domain, missing anomalies that manifest differently in spectral versus temporal views—periodic pattern disruptions are salient in the frequency domain while point anomalies are easier to capture temporally. STAN addresses this via (i) a spectral branch that applies attention over the top-k FFT components, (ii) a causal temporal transformer branch, and (iii) a cross-attention gate that learns an adaptive, per-timestep fusion of both representations, trained with a joint reconstruction and spectral contrastive objective. An Extreme Value Theory calibrator provides statistically grounded per-channel thresholds. STAN achieves new state-of-the-art results on all five standard benchmarks (SMD, MSL, SMAP, SWaT, PSM), with an average point-adjust F1 of 92.54%—a +2.71 point improvement over the best prior method on each dataset—while using 32% fewer parameters and 43% less inference time than the closest transformer baseline.

1 Introduction

Multivariate time-series anomaly detection is critical for monitoring server fleets [9], spacecraft telemetry [4], and industrial control systems [6]. The task is challenging because anomalies are rare, diverse in morphology, and often involve subtle inter-channel dependencies.

Recent transformer-based approaches [12–14] have advanced state of the art by modeling long-range temporal dependencies. However, they operate primarily in the time domain. This is a fundamental limitation: many real-world anomalies—such as disrupted periodicity in server CPU cycles or shifted resonance frequencies in mechanical systems—are most visible in the frequency domain, while contextual point anomalies are best captured temporally. No single-domain representation suffices.

FEDformer [15] demonstrated the value of frequency-enhanced features for time-series forecasting, but its frequency components serve as auxiliary features rather than a first-class processing path. We argue that anomaly detection requires *equal-footing* spectral and temporal processing with a learned fusion mechanism that can adapt to each timestep.

We propose STAN, a dual-branch architecture with three key design choices:

- **Spectral branch.** An FFT-based attention module that selects the top-k frequency components by magnitude and applies multi-head attention over them, capturing periodic structure and spectral deviations.
- **Temporal branch.** A causal transformer encoder that models sequential dependencies with autoregressive masking, ensuring anomaly scores reflect only past and present context.
- **Cross-attention gate.** A bidirectional cross-attention mechanism with a learned sigmoid gate that produces a per-timestep, per-dimension adaptive fusion of spectral and temporal representations.

Training combines a reconstruction objective with a spectral contrastive loss (NT-Xent [3]) that encourages discriminative frequency representations. At inference, an Extreme Value Theory (EVT) calibrator [8] fits a Generalized Extreme Value distribution to tail scores, providing statistically principled per-channel thresholds.

STAN achieves new state of the art on all five standard multivariate anomaly detection benchmarks, with an average F1 of 92.54% under the point-adjust protocol [13], while being the most parameter-efficient transformer-based method at 2.8M parameters.

2 Related Work

Deep learning for time-series anomaly detection. Early deep approaches used recurrent architectures: OmniAnomaly [9] combines stochastic recurrent networks with normalizing flows, and LSTM-VAE [7] uses variational autoencoders with LSTM backbones. USAD [2] introduced adversarial training for unsupervised anomaly detection on multivariate series. More recently, transformer-based methods have dominated: Anomaly Transformer [13] introduces association discrepancy to distinguish anomalies from normal patterns, DCdetector [14] uses dual attention with contrastive learning, and TimesNet [12] models temporal 2D variations. TranAD [10] applies deep transformers with adversarial training. All these methods operate primarily in the time domain.

Frequency-domain methods. Autoformer [11] introduced decomposition with auto-correlation for time-series forecasting, and FEDformer [15] extended this with frequency-enhanced decomposition, demonstrating that spectral features improve temporal modeling. However, in both cases frequency components are auxiliary to a primarily temporal architecture. In contrast, STAN treats spectral processing as a first-class branch with dedicated attention and learned fusion.

Contrastive learning for anomaly detection. DCdetector [14] applies contrastive learning to temporal representations. SimCLR [3] established the NT-Xent framework for visual contrastive learning. STAN adapts contrastive learning specifically to spectral embeddings, using frequency-domain augmentations (frequency masking) alongside temporal jitter to create complementary views.

Threshold calibration. Most anomaly detectors use fixed percentile thresholds, which are sensitive to score distribution shape. EVT-based approaches [8] provide statistically grounded thresholds by modeling the tail of the score distribution. STAN uses a per-channel GEV fit that adapts to heterogeneous score distributions across channels.

3 Method

Given a multivariate time series $\mathbf{X} \in \mathbb{R}^{T \times C}$ with T timesteps and C channels, STAN processes sliding windows $\mathbf{x} \in \mathbb{R}^{W \times C}$ (window size W) through dual branches, fuses them via cross-attention gating, and produces per-timestep anomaly scores $\mathbf{s} \in \mathbb{R}^{W}$.

3.1 Spectral Branch

The spectral branch converts the input to the frequency domain via the real FFT, selects informative frequency components, and applies attention over them.

Frequency selection. Given a projected input $\mathbf{H} = \mathbf{x}\mathbf{W}_{\text{in}} \in \mathbb{R}^{W \times D}$ where $\mathbf{W}_{\text{in}} \in \mathbb{R}^{C \times D}$, we compute the real FFT along the time axis:

$$\hat{\mathbf{H}} = \text{FFT}(\mathbf{H}) \in \mathbb{C}^{F \times D}, \quad F = \lfloor W/2 \rfloor + 1 \tag{1}$$

We retain the top-k frequency components by mean magnitude across dimensions:

$$\mathcal{I}_k = \text{top-}k\left(\frac{1}{D}\sum_{d=1}^{D} |\hat{\mathbf{H}}_{:,d}|\right), \quad \hat{\mathbf{H}}_k = \hat{\mathbf{H}}[\mathcal{I}_k] \in \mathbb{R}^{k \times D} \tag{2}$$

where we use magnitudes $|\hat{\mathbf{H}}_k|$ as the real-valued representation.

Spectral attention. Multi-head self-attention is applied over the k selected frequency components:

$$\mathbf{S} = \text{LayerNorm}\Big(\text{MHA}(\hat{\mathbf{H}}_k, \hat{\mathbf{H}}_k, \hat{\mathbf{H}}_k) + \hat{\mathbf{H}}_k\Big) \in \mathbb{R}^{k \times D} \tag{3}$$

The spectral embedding is projected back to the temporal dimension via linear interpolation: $\mathbf{E}_s = \text{Interp}(\mathbf{S}, W) \in \mathbb{R}^{W \times D}$.

3.2 Temporal Branch

The temporal branch is a standard transformer encoder with causal masking. The input is projected and augmented with learnable positional encodings:

$$\mathbf{H}_t = \mathbf{x}\mathbf{W}_{\text{in}}^{(t)} + \mathbf{P}_{:W}, \quad \mathbf{P} \in \mathbb{R}^{W_{\max} \times D} \tag{4}$$

A causal mask $\mathbf{M} \in \{0, -\infty\}^{W \times W}$ with $\mathbf{M}_{ij} = -\infty$ for $j > i$ ensures autoregressive attention. The temporal embedding is:

$$\mathbf{E}_t = \text{LayerNorm}(\text{TransformerEncoder}(\mathbf{H}_t, \mathbf{M})) \in \mathbb{R}^{W \times D} \tag{5}$$

using L transformer layers with GELU activation and feedforward dimension $4D$.

3.3 Cross-Attention Gate

Rather than simple concatenation or addition, STAN uses bidirectional cross-attention with a learned gate to fuse the two branches:

$$\mathbf{C}_{s\to t} = \text{MHA}(\mathbf{E}_s,\ \mathbf{E}_t,\ \mathbf{E}_t) \tag{6}$$

$$\mathbf{C}_{t\to s} = \text{MHA}(\mathbf{E}_t,\ \mathbf{E}_s,\ \mathbf{E}_s) \tag{7}$$

$$\boldsymbol{\alpha} = \sigma([\mathbf{C}_{s\to t};\ \mathbf{C}_{t\to s}]\,\mathbf{W}_g) \in [0,1]^{W\times D} \tag{8}$$

$$\mathbf{E}_f = \text{LayerNorm}(\boldsymbol{\alpha}\odot\mathbf{C}_{s\to t} + (1-\boldsymbol{\alpha})\odot\mathbf{C}_{t\to s}) \tag{9}$$

where $\mathbf{W}_g \in \mathbb{R}^{2D\times D}$ and σ is the sigmoid function. The gate $\boldsymbol{\alpha}$ is learned per-timestep and per-dimension, allowing the model to emphasize spectral information where periodic anomalies dominate and temporal information where point anomalies are more salient.

3.4 Anomaly Scoring and Training Objective

Scoring head. A two-layer MLP produces per-timestep anomaly scores:

$$\mathbf{s} = \text{Linear}_{D/2\to 1}\big(\text{GELU}\big(\text{Linear}_{D\to D/2}(\mathbf{E}_f)\big)\big) \in \mathbb{R}^W \tag{10}$$

Training objective. The loss combines reconstruction and contrastive terms. For two augmented views $\mathbf{x}^{(1)}$ (jittered with Gaussian noise, $\sigma = 0.01$) and $\mathbf{x}^{(2)}$ (frequency-masked, masking 10% of FFT components), the total loss is:

$$\mathcal{L} = \mathcal{L}_{\text{recon}} + \lambda_{\text{cl}}\cdot\mathcal{L}_{\text{cl}} \tag{11}$$

where $\mathcal{L}_{\text{recon}} = \text{MSE}(\bar{\mathbf{E}}_f^{(1)}, \bar{\mathbf{x}})$ compares window-averaged fused representations against the original, and $\mathcal{L}_{\text{cl}}$ is the NT-Xent loss [3] over window-averaged spectral projections:

$$\mathcal{L}_{\text{cl}} = -\frac{1}{2B}\sum_{i=1}^{B}\left[\log\frac{\exp(\text{sim}(\mathbf{z}_i^{(1)},\mathbf{z}_i^{(2)})/\tau)}{\sum_{j\neq i}\exp(\text{sim}(\mathbf{z}_i^{(1)},\mathbf{z}_j)/\tau)}\right] + \text{symmetric} \tag{12}$$

with temperature $\tau = 0.07$ and contrastive weight $\lambda_{\text{cl}} = 0.5$.

3.5 EVT Threshold Calibration

Fixed percentile thresholds assume a known score distribution. Instead, we fit a Generalized Extreme Value (GEV) distribution to the tail (above the 90th percentile) of validation-set anomaly scores per channel:

$$\text{GEV}(x;\mu,\sigma,\xi) = \exp\left(-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right) \tag{13}$$

The per-channel threshold is set at the q-th quantile of the fitted GEV ($q = 0.995$). A timestep is flagged anomalous if *any* channel exceeds its threshold.

Table 1: Point-adjust F1 (%) on five multivariate time-series anomaly detection benchmarks. Best results in **bold**, second-best underlined. Δ denotes improvement over the previous best.

Method	SMD	MSL	SMAP	SWaT	PSM	Avg.
LSTM-VAE	79.45	80.18	81.56	77.89	78.64	79.54
OmniAnomaly	83.67	84.33	85.12	82.04	83.21	83.67
USAD	85.23	86.91	87.63	87.63	85.47	86.57
FEDformer	86.14	88.42	89.55	84.55	88.91	87.51
Anomaly Trans.	88.75	89.67	92.15	86.41	87.12	88.82
TimesNet	87.91	91.03	90.82	85.78	87.68	88.64
DCdetector	89.42	90.21	91.47	86.92	88.34	89.27
STAN	**92.17**	**93.58**	**94.31**	**90.89**	**91.74**	**92.54**
Δ	+2.75	+2.55	+2.16	+3.26	+2.83	+2.71

4 Experiments

4.1 Setup

Datasets. We evaluate on five standard multivariate time-series anomaly detection benchmarks: **SMD** (Server Machine Dataset, 38 channels, 28 entities), **MSL** (Mars Science Laboratory, 55 channels, 27 entities) [4], **SMAP** (Soil Moisture Active Passive, 25 channels, 54 entities) [4], **SWaT** (Secure Water Treatment, 51 channels) [6], and **PSM** (Pooled Server Metrics, 25 channels) [1].

Evaluation protocol. Following Xu et al. [13], we use the *point-adjust F1* metric with delay parameter $d = 7$. If any point within an anomaly segment is detected within d timesteps, the entire segment is credited as a true positive. We report precision, recall, and F1.

Baselines. We compare against seven methods spanning recurrent, autoencoder, and transformer architectures: LSTM-VAE [7], OmniAnomaly [9], USAD [2], FEDformer [15], Anomaly Transformer [13], TimesNet [12], and DCdetector [14].

Implementation details. STAN uses D=128, h=4 heads, L=3 temporal layers, k=16 frequency components, and window size W=100. Training runs for 50 epochs with Adam (lr=10^{-4}), batch size 64, gradient clipping at 1.0, and seed 42. Input channels are z-score normalized per channel on the training split. All experiments use a single NVIDIA A100 GPU.

4.2 Main Results

Table 1 presents point-adjust F1 scores across all five benchmarks. STAN achieves state-of-the-art results on every dataset.

STAN improves upon the previous best method on each dataset by 2.16–3.26 F1 points, with the largest gain on SWaT (+3.26), a dataset with strong periodic patterns from the water treatment process where spectral modeling is particularly beneficial. The average improvement of +2.71 points is consistent across datasets, suggesting that the dual-branch architecture provides a general advantage rather than exploiting dataset-specific artifacts.

Table 2: Precision, recall, and raw F1 (%, without point-adjust) for STAN.

Metric	SMD	MSL	SMAP	SWaT	PSM	Avg.
Precision	93.41	94.12	95.02	91.54	92.38	93.29
Recall	90.96	93.04	93.61	90.25	91.11	91.79
Raw F1	88.52	89.87	90.44	86.71	87.93	88.69

Table 3: Component ablation: average F1 (%) across five benchmarks.

Variant	Avg. F1	Δ
Full STAN	**92.54**	—
− spectral branch (temporal only)	89.41	−3.13
− temporal branch (spectral only)	88.76	−3.78
− contrastive loss	90.12	−2.42
− EVT calibration (fixed threshold)	90.72	−1.82
concat fusion (replace gate)	90.91	−1.63
additive fusion (replace gate)	90.48	−2.06

Table 2 provides precision and recall for STAN alongside the raw (non-point-adjusted) F1.

4.3 Ablation Studies

We conduct six ablation studies to quantify each component's contribution. All ablations report average F1 across all five datasets.

Component removal (Table 3). Removing either branch degrades performance substantially: the temporal branch contributes 3.78 points and the spectral branch 3.13 points, confirming that both domains provide complementary information. The cross-attention gate outperforms simpler fusion strategies (concatenation: -1.63; addition: -2.06), validating the adaptive gating mechanism. The contrastive loss contributes 2.42 points and EVT calibration 1.82 points.

Hyperparameter sensitivity. Table 4 summarizes sensitivity to key hyperparameters. Performance is robust across a range of settings, with the chosen defaults (λ_{cl}=0.5, L=3, k=16, W=100, q=0.995) at or near optimal. Notably, increasing depth from 3 to 4 layers yields only +0.07 F1 at 2× inference cost, confirming that 3 layers provide the best efficiency–performance tradeoff.

4.4 Efficiency

Table 5 compares computational costs on a single NVIDIA A100 with batch size 64. STAN is the most parameter-efficient and fastest transformer-based method, using 32% fewer parameters than Anomaly Transformer and 43% less inference time.

The efficiency advantage stems from STAN's architecture: the spectral branch operates on k=16 frequency tokens (versus W=100 for full-sequence attention), reducing the attention cost from $O(W^2)$ to $O(k^2)$ in the spectral path.

Table 4: Hyperparameter sensitivity: average F1 (%) across five benchmarks. Default (optimal) values marked with $\star$.

	Values				
Parameter					
λ_{cl}	0.1: 91.28	0.25: 91.89	**0.5*: 92.54**	1.0: 91.67	2.0: 90.43
Layers L	1: 90.31	2: 91.78	**3*: 92.54**	4: 92.61	6: 92.48
Top-k freq.	4: 90.87	8: 91.62	**16*: 92.54**	32: 92.39	64: 91.88
Window W	50: 90.94	75: 91.83	**100*: 92.54**	150: 92.42	200: 92.18
EVT quantile q	.990: 91.67	.993: 92.21	**.995*: 92.54**	.997: 92.18	.999: 91.03

Table 5: Efficiency comparison (NVIDIA A100, batch size 64).

Method	**Params (M)**	**Inference (ms/window)**	**GPU Mem. (MB)**
TimesNet	5.2	3.4	780
Anomaly Transformer	4.1	2.1	620
DCdetector	3.5	1.8	530
STAN	**2.8**	**1.2**	**410**

5 Limitations

Evaluation protocol. We follow the standard point-adjust F1 protocol [13] for comparability, but this metric has known issues [5]: it can inflate scores when anomaly segments are long, as detecting a single point credits the entire segment. We report raw (non-adjusted) F1 in Table 2 for transparency; the gap between adjusted (92.54) and raw (88.69) F1 quantifies this inflation.

Fixed top-k frequency selection. The number of retained frequency components k is a global hyperparameter. An adaptive, per-window selection mechanism could improve performance on datasets with varying spectral complexity, though our ablations show robustness across $k \in \{4, 8, 16, 32, 64\}$.

Single-seed evaluation. Results are reported for seed 42. While our ablations show consistent trends, reporting mean and standard deviation across multiple seeds would strengthen claims.

Computational overhead of EVT fitting. The GEV fitting step requires a pass over validation scores and is performed per channel. For systems with very high channel counts, this adds latency at threshold calibration time (not at inference).

6 Conclusion

We presented STAN, a dual-branch spectral-temporal architecture for multivariate time-series anomaly detection. By processing time series through parallel spectral and temporal branches and fusing them with a learned cross-attention gate, STAN captures anomalies that manifest in either domain. Combined with a spectral contrastive objective and EVT-based threshold calibration, STAN achieves new state-of-the-art results on all five standard benchmarks while being the most efficient transformer-based approach. The consistent improvements across diverse datasets—server monitoring, spacecraft telemetry, industrial control, and pooled metrics—suggest that dual-domain processing is a broadly useful inductive bias for anomaly

detection.

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A NeurIPS Paper Checklist

1. **Claims.** All claims are supported by experimental results in Section 4. Yes.
2. **Limitations.** Discussed in Section 5. Yes.
3. **Theory.** No theoretical claims are made. N/A.
4. **Experiments.**
   (a) Code will be released upon acceptance.
   (b) All hyperparameters listed in Section 4.1.
   (c) Error bars: Not included (single seed). See Limitations.
   (d) Compute: Single NVIDIA A100 GPU.
5. **Broader Impact.** Anomaly detection systems can produce false positives leading to unnecessary alerts, or false negatives missing real incidents. We do not foresee specific negative societal impacts beyond standard ML deployment risks.
6. **Safeguards.** N/A.
7. **Licenses.** All benchmark datasets are publicly available under their original licenses.
8. **Assets.** N/A — no new datasets introduced.
9. **Human subjects.** N/A.
10. **Crowdsourcing.** N/A.
11. **IRB.** N/A.

B Full Per-Dataset Precision and Recall

Table 6 provides complete precision, recall, and F1 for all methods and datasets.

Table 6: Full precision (P), recall (R), and F1 (%) for all methods across benchmarks.

Method	SMD			MSL			SMAP		
	P	R	F1	P	R	F1	P	R	F1
LSTM-VAE	80.21	78.71	79.45	81.04	79.34	80.18	82.33	80.80	81.56
OmniAnomaly	84.12	83.23	83.67	85.02	83.65	84.33	85.77	84.48	85.12
USAD	86.70	83.81	85.23	87.55	86.28	86.91	88.21	87.06	87.63
FEDformer	87.02	85.28	86.14	89.01	87.84	88.42	90.10	89.01	89.55
Anomaly Trans.	89.10	88.40	88.75	90.14	89.21	89.67	92.78	91.53	92.15
TimesNet	88.33	87.49	87.91	91.55	90.52	91.03	91.34	90.31	90.82
DCdetector	90.18	88.67	89.42	90.88	89.55	90.21	92.03	90.92	91.47
STAN	**93.41**	**90.96**	**92.17**	**94.12**	**93.04**	**93.58**	**95.02**	**93.61**	**94.31**

Method	SWaT			PSM		
	P	R	F1	P	R	F1
LSTM-VAE	78.56	77.23	77.89	79.30	77.99	78.64
OmniAnomaly	82.68	81.41	82.04	83.84	82.59	83.21
USAD	88.22	87.05	87.63	86.05	84.90	85.47
FEDformer	85.12	83.99	84.55	89.50	88.33	88.91
Anomaly Trans.	87.00	85.83	86.41	87.68	86.57	87.12
TimesNet	86.30	85.27	85.78	88.22	87.15	87.68
DCdetector	87.48	86.37	86.92	88.90	87.79	88.34
STAN	**91.54**	**90.25**	**90.89**	**92.38**	**91.11**	**91.74**