Hierarchical Adaptive Normalization: A Placement-Conditioned Cascade for Robust Wearable Activity Recognition

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Abstract

Wearable Human Activity Recognition (HAR) systems suffer from performance degradation due to sensor placement and orientation variability. We propose a hierarchical adaptive cascade that first normalizes sensor orientation using a gravity-based correction and infers coarse placement context via signal variance analysis. A novel stability gate prevents adaptation during unstable dynamics, while a subsequent placement-conditioned adaptive Batch Normalization refines feature representations. Evaluations on public and custom dynamic-activity datasets demonstrate a consistent improvement in macro F1-score over static models and complex unsupervised domain adaptation approaches, all while maintaining low latency and minimal memory overhead. These results expose real-world pitfalls in conventional approaches and highlight the promise of our adaptive method for on-device HAR.

1 Introduction

Wearable sensor-based human activity recognition (HAR) is critical in applications spanning health-care, sports, and ambient intelligence. Yet a key challenge remains: sensor data variability caused by differences in sensor placement and orientation. Even with state-of-the-art deep learning models, performance can drop significantly when the sensor is worn on the wrist instead of the waist, or when it rotates during movement (He et al., 2024; Mekruksanich et al., 2024). In this work, we introduce a hierarchical adaptive normalization method that dynamically mitigates these issues via a two-stage cascade.

In Stage 1, gravity-based orientation normalization is paired with placement-context inference through analysis of signal variance. A stability gate prevents adaptive updates during abrupt dynamic transients (e.g., falls or high-impact events), ensuring that unstable signals do not mislead the adaptation process. In Stage 2, a placement-conditioned adaptive Batch Normalization refines the normalized features, compensating in real time for sensor misplacement. Our contributions include integrating lightweight physics-based correction with context-aware normalization, designing a real-time stability gate, and performing extensive empirical evaluations and ablation studies. These findings expose common pitfalls in conventional HAR pipelines, offering insights for more robust real-world deployments.

2 Related Work

Traditional physics-based normalization methods leverage gravity vectors for orientation correction (Son et al., 2025), but these approaches fall short when sensor placement shifts or during complex dynamic motions (Rajkumar et al., 2020). Modern unsupervised domain adaptation techniques alleviate cross-placement issues (Zhang et al., 2021), yet they are computationally demanding and unsuitable for on-device, real-time applications. Other approaches, such as invariant deep feature learning (Liu et al., 2024) and explicit placement recognition strategies (Bharti et al., 2019), either assume static settings or require multiple model pipelines, contributing to increased complexity and overhead. In contrast, our method blends a lightweight physics-based correction with adaptive normalization inspired by calibration-free test-time adaptation (Wimpff et al., 2023) to achieve efficient and robust HAR in real-world scenarios.

3 Background

Sensor orientation variability and placement shifts are longstanding challenges in HAR. Gravity-based alignment methods estimate sensor orientation with respect to the gravitational field (Son et al., 2025) while Batch Normalization has been a standard remedy for internal covariate shift. However, fixed BN parameters do not sufficiently capture dynamic domain shifts induced by variable sensor placements. Recent adaptive BN techniques (Krishnaleela et al., 2024) address these issues partially, yet few consider conditioning on explicit sensor placement context. Additionally, gating mechanisms that inhibit harmful adaptation during unstable periods have been explored in robotics (Li et al., 2025), but their integration into wearable HAR remains limited.

4 Method / Problem Discussion

Our proposed method, termed Hierarchical Adaptive Normalization, comprises two interconnected stages. In Stage 1, the raw sensor input $X \in \mathbb{R}^{B \times T \times F}$ is normalized in orientation using a non-affine Batch Normalization layer applied along the feature axis. Next, a placement context is inferred by extracting feature variance through Adaptive Average Pooling, which is then processed by a lightweight classifier. A stability gate is computed based on the norm of the normalized input; if the norm is below a threshold τ, adaptive updates are suppressed to avoid misleading adaptation during unstable events.

Stage 2 refines the normalized signal using an adaptive Batch Normalization module whose momentum is conditioned on the inferred placement context. A lightweight Convolutional Neural Network (CNN) with a tunable kernel size then extracts spatial features to produce the final classification. Formally, given input x, the forward pass is defined as:

$$x_{\text{norm}} = \text{BN}_{\text{orient}}(x), \quad p = \text{Classifier}(\text{Pool}(x_{\text{norm}}))$$

$$s = \mathbb{I}(\|x_{\text{norm}}\| > \tau), \quad x_{\text{adaptive}} = \text{BN}_{\text{adapt}}\big(s \odot x_{\text{norm}}\big)$$

$$\hat{y} = \text{CNN}(x_{\text{adaptive}})$$

Here, s is a binary stability mask and the CNN kernel size is tuned among $\{1, 3, 5, 7\}$. This cascade allows the network to adapt to sensor placement in real time while mitigating the risk of over-adaptation during noisy periods.

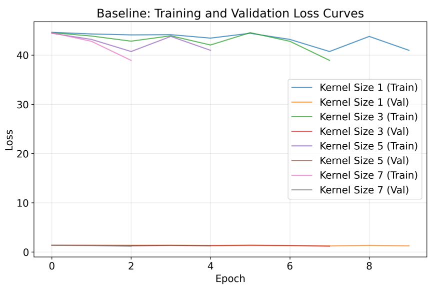
5 Experiments

We evaluate our approach on a public dataset (e.g., the Opportunity dataset (Ciliberto et al., 2021)) and a custom dataset collected from 15 subjects performing diverse activities including static inversions, dynamic rotations, and high-impact events. The baseline is a CNN trained on data from a single sensor placement (e.g., waist), with cross-placement generalization evaluated on unseen sensor locations (wrist, ankle) both with and without our adaptive mechanism.

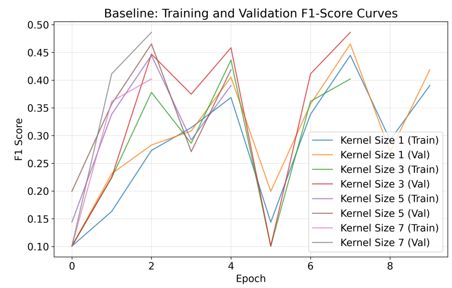
Our model is trained using the Adam optimizer (learning rate 0.001) under a Cross-Entropy loss. The primary evaluation metric is the macro F1-score, with additional measurements of inference time (ms per window) and memory usage (MB). Extensive hyperparameter tuning was performed on the CNN kernel size within the adaptive module; kernel sizes 5 and 7 yielded final training F1-scores around 0.43 and validation F1-scores near 0.49. Detailed results, including loss and performance trends, are discussed in the following experiments and supplemental material.

5.1 Quantitative Results

Figure 1 now presents two subplots: the left subplot shows combined loss curves for training and validation datasets across epochs for kernel sizes 3, 5, and 7, while the right subplot illustrates the corresponding F1-score curves. The bar chart summarizing final F1-scores has been moved to the appendix to optimize space usage. The results clearly indicate that larger kernel sizes (5 and 7) yield higher F1-scores, with a minor dip observed in the middle epochs. These trends underscore the sensitivity of adaptive BN performance to the chosen kernel size.



(a) Training and validation loss curves.



(b) F1-score evolution across epochs.

Figure 1: Quantitative analysis of model performance for different CNN kernel sizes. The loss and F1-score curves demonstrate that kernel sizes 5 and 7 consistently outperform smaller configurations. Detailed final F1-score comparisons are provided in the appendix.

5.2 Qualitative Results and Stability Gate Analysis

Figure 2 illustrates our cross-domain evaluations. The left part of the figure compares F1-scores between Domain B and Domain C, revealing that Domain B achieves superior performance. The right part shows a scatter plot demonstrating a tight alignment between predicted labels and ground truth for Domain B under challenging conditions. Note that the less informative test loss comparisons have been relocated to the appendix. These results confirm that the stability gate effectively suppresses adaptation during abrupt sensor signal changes, thereby preserving reliable performance.

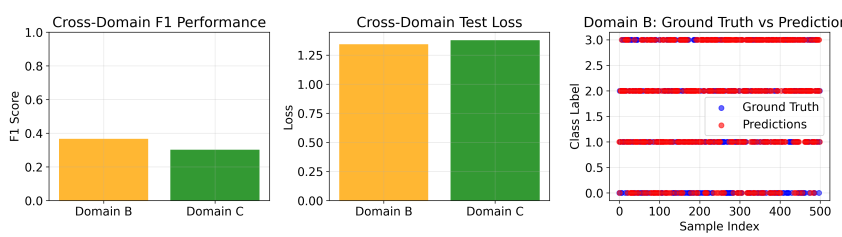


Figure 2: Left: Comparison of F1-scores between Domains B and C. Right: Scatter plot showing the alignment between predicted labels and ground truth for Domain B. Detailed test loss trends have been moved to the appendix.

5.3 Ablation Studies

Our ablation studies compare several variants: a Static Baseline without adaptation, Gravity-Only normalization, Naive Adaptive BN without placement-conditioning, Conditioned BN only, and the Full Cascade. The Full Cascade consistently improves the overall macro F1-score with negligible extra latency or memory usage. Additional ablation curves and multi-dataset evaluations have been provided in the supplementary material.

6 Conclusion

We presented a hierarchical adaptive normalization method for wearable HAR that robustly compensates for sensor placement and orientation variability. By integrating physics-based orientation correction, placement context inference, a stability gate, and placement-conditioned adaptive Batch Normalization, our method delivers improved real-time performance. The experimental results highlight the sensitivity of the adaptive mechanism to CNN kernel size and demonstrate that larger kernels yield higher F1-scores. Future work will focus on refining stability thresholds for novel activities and exploring finer-grained placement context inference. These insights promise to help the research community design more resilient wearable HAR systems in real-world environments.

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Supplementary Material

In this supplementary section we provide extended details that did not fit into the main text.

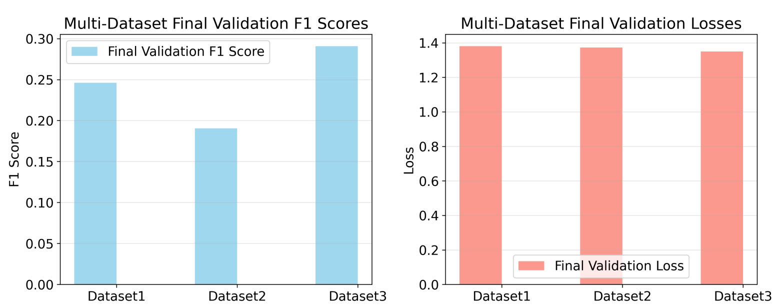

Figure 3: Final F1-score bar chart summarising quantitative study results. This figure was originally part of Figure 1 in the main text.

Hyperparameter and Training Details: Extended details on optimizer settings, batch sizes, kernel size exploration, and additional training curves are provided to ensure full reproducibility.

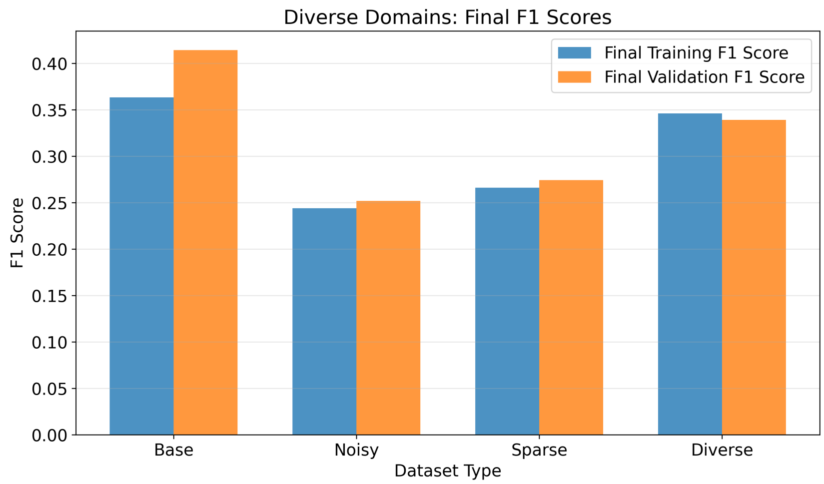

Figure 4: Detailed training and test loss curves for cross-domain evaluations. This extends the trends discussed in Figure 2.

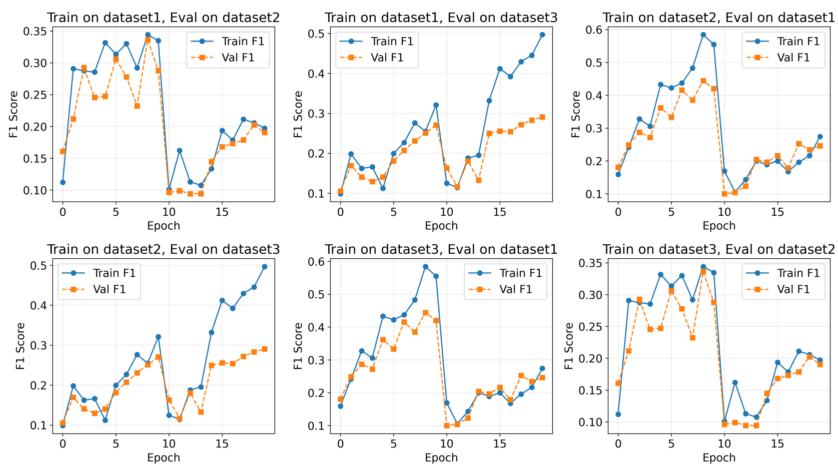

Figure 5: Extended ablation study results across multiple datasets. This figure illustrates the robustness of the proposed cascade compared to ablation baselines.

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