MBFAD: Benchmarking Balance Function Assessment with Environmental Perturbation and Synergistic Tasks

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Abstract. Balance function assessment is vital for proactive health monitoring and fall prevention. However, conventional clinical methods are heavily influenced by subjective judgment, leading to potential inconsistencies in evaluation. While the rapid development of wearable technology has provided a significant research hotspot for objective monitoring, current methods rarely identify stability states through activity semantics. Furthermore, the lack of publicly available datasets containing true imbalance states severely hinders the development of robust assessment models. To address these challenges, we introduce MBFAD, a multi-modal benchmark encompassing a ternary paradigm of static, dynamic, and reactive balance activities. MBFAD collects synchronized whole-body kinematics and plantar pressure data from 29 subjects and induces true imbalance states using an environmental perturbation scheme. Based on this, we propose the M^2-Balance Framework, a synergistic multi-task architecture for joint activity recognition and stability analysis. Within M^2-Balance, the HSConv module captures multi-scale features through recursive convolution to provide semantic priors, while the CSConv module utilizes an expected channel damage matrix to mitigate high-dimensional redundancy and identify stability-sensitive channels. Experimental results on SisFall, PDS and MBFAD datasets demonstrate that M^2-Balance outperforms existing models, establishing a fundamental paradigm for modeling synergistic activities and stability in the Balance function assessment domain. The code and dataset will be released at https://github.com/huaingyingqin/MBFAD.

Keywords: Wearable sensor · Multi-modal Dataset · Human Balance Function Assessment · Human Activity Recognition.

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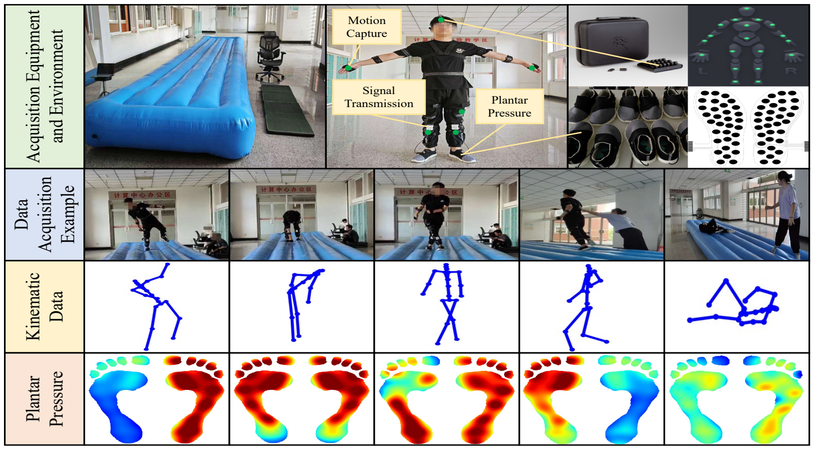

Fig. 1. MBFAD Showcase. (Top-left) Experimental environment. (Top-center) Demonstration of device wear. (Top-right) Sensor distribution of the device. (Second row) The subject performs the activity. (Third row) PN3 tracks kinematics data from 59 body parts. (Fourth row) Plantar pressure distribution is measured by 32 sensors per shoe.

1 Introduction

The preservation of balance is fundamental to individual functional independence and overall quality of life [14]. The primary modalities for assessing balance include clinical scales, motion capture, and plantar pressure analysis. Clinical instruments like the Berg Balance Scale serve as diagnostic tools but are inherently limited to snapshot observations in controlled settings, failing to account for the stochastic nature of balance loss [14]. While kinematic systems provide detailed joint coordination data, they often lack the ground-reaction force information critical for stability analysis. Plantar pressure monitoring offers direct insights into the Center of Pressure but lacks the skeletal context required to interpret the user's motor intent. These limitations lead to interpretative difficulties in complex daily activities, where the lack of synchronized multi-modal data makes it challenging to distinguish purposeful movement from genuine instability.

Recently, human motion analysis and rehabilitation based on wearable sensors have flourished, with deep learning advancing the extraction of discriminative features from biomechanical signals. For instance, Song et al. [20] proposed a "weak foot" feature for fall risk assessment using multi-dimensional Center of Pressure data, while Wu et al. [24] addressed inter-individual pressure differences through the MhNet's multi-scale spatio-temporal features. Similarly, Tang et al. [22] introduced a hierarchical split module to enhance feature representation efficiently , and Yang et al. [25] developed the MFCANN framework to fuse local and global cues via multi-feature attention. However, most of these studies remain bifurcated, focusing either on identifying movement types through Human Activity Recognition (HAR) or on post-hoc Fall Detection, which fails to provide a synergistic, pre-emptive stability assessment. Furthermore, existing research lacks benchmark datasets capable of synchronizing high-fidelity kinematics with plantar pressure distributions under conditions of authentic postural instability.

To address these issues, we introduce the Multi-modal Balance Function Assessment Dataset (MBFAD). MBFAD features synchronized kinematic data from 59 body parts and plantar pressure distributions collected from 29 subjects. By employing an environmental perturbation protocol to induce authentic postural instability, MBFAD serves as a potential benchmark for research in deep learning-based balance analysis. Furthermore, to tackle the inherent contextual dependency in biomechanical signals, we present the Multi-modal Multi-task Balanced Function Assessment Framework ($\mathbf{M^2}$-Balance). $\mathbf{M^2}$-Balance is a multi-task network that establishes human activity recognition as a prior task for balance function assessment (BFA). Extensive experiments demonstrate that $\mathbf{M^2}$-Balance surpasses previous state-of-the-art networks on the multiple datasets. Ablation experiments also confirm the effectiveness of each component, particularly the synergy between activity context and stability assessment.

Table 1. Main datasets relevant to the balance function assessment and their analysis.

Dataset	Sub	Act	Locat	Kinem	Press	React	Perturb
PAMAPL [17]	9	18	WR, CH, AN	✔	✘	✘	✘
OPPORTUNITY [3]	4	17	AR, FA, BA, FT	✔	✘	✘	✘
UCI-HAR [1]	30	6	WA	✔	✘	✘	✘
USC-HAD [26]	14	12	HP	✔	✘	✘	✘
UniMiB SHAR [13]	30	17	PK	✔	✘	✘	✘
SisFall [21]	38	34	WA	✔	✘	✔	✘
WISDM [10]	29	6	PK	✔	✘	✘	✘
BDS [18]	163	1	PL	✘	✔	✘	✔
Lin [11]	18	1	PL	✘	✔	✘	✘
Smart-Insole [2]	29	12	PL	✘	✔	✘	✘
PlantPre [7]	48	1	PL	✘	✔	✘	✘
PDS [19]	49	1	WB	✔	✔	✘	✔
UP-Fall [12]	17	11	HP, NK, WA, WR, AN	✔	✘	✘	✘
Berkel MHAD [15]	12	11	WR, HP, AN	✔	✘	✘	✘
Mmact [9]	20	37	PK, WR	✔	✔	✔	✘
MBFAD	**29**	**14**	**WB**	✔	✔	✔	✔

* Sub: Subjects, Act: Activities, Locat: Sensor Location, Kinem: Kinematic Data, Press: Plantar Pressure, React: Reactive Activities, Perturb: Sensory Perturbation.

* AR: Arm, AN: Ankle, BA: Back, CH: Chest, FA: Forward Arm, FT: Foot, HP: Hip, NK: Neck, PK: Pocket, PL: Plantar, UL: Upper Leg, WA: Waist, WR: Wrist, WB: Whole Body.

2 MBFAD

2.1 Overview

As shown in Table 1, we summarize and analyze the limitations of 15 motion-related datasets to construct the MBFAD dataset. Fig. 1 shows the experimental environment, acquisition equipment, acquisition examples, and kinematic and plantar pressure modal data. The MBFAD dataset includes 29 subjects (15 males, age 21.73 ± 2.02 years; 14 females, age 20.71 ± 1.53 years). Each subject completes 14 activities under normal and sensory perturbation conditions, with each activity repeated 3 times, for a total of 2,436 samples collected.

2.2 Data Acquisition and Annotations

The MBFAD dataset uses a PN3 system (16 wireless nine-axis IMUs, sampling frequency 60 Hz) and JiBuEn smart gait shoes (32 sensors per shoe, sampling frequency 50 Hz) for simultaneous kinematic and plantar pressure acquisition. It is important to note that these 16 IMUs are physical devices, while the 59 body parts are based on a human skeletal model, with kinematic nodes calculated from the sensor data. Two rehabilitation experts (with approximately 8 years of experience) jointly develop 14 activities (static standing, jumping, pushed while walking, etc.) based on clinical scales (Berg Scale, Brunel Scale) and the daily activities of elderly, comprehensively covering static, dynamic, and reactive balance assessments.

To induce genuine postural instability in participants, we construct an unstable support surface using an air cushion of $10\,\mathrm{m} \times 2\,\mathrm{m} \times 0.4\,\mathrm{m}$ to increase the difficulty of postural control and induce compensatory balance responses [6, 23]. Each subject completes 14 activities under both flat ground and air cushion conditions to induce postural adjustment behaviors. Accordingly, BFA labels are defined as normal and imbalance state, with the flat ground test corresponding to the normal state and the air cushion test corresponding to the unbalanced state. The entire process strictly adheres to ethical standards and ensures complete and high-quality samples through rigorous hardware calibration and data resampling.

3 Methods

3.1 Balance Function Assessment Task Definition

The primary distinction between HAR and BFA lies in their objectives: HAR identifies categorical motor patterns, whereas BFA evaluates postural stability to estimate fall risk levels.

Given multi-modal features from S modalities, denoted as $\mathbf{H} \in \mathbb{R}^{S \times L}$, where L represents the number of time steps within each sliding window, and $\mathbf{H} = [\mathbf{h}^{(1)}, \ldots, \mathbf{h}^{(S)}]^\top$, the assessment task is formulated as a mapping $\mathcal{P}$:

$$\hat{y} = \mathcal{P}(\mathit{\Gamma}(\mathbf{H})) \tag{1}$$

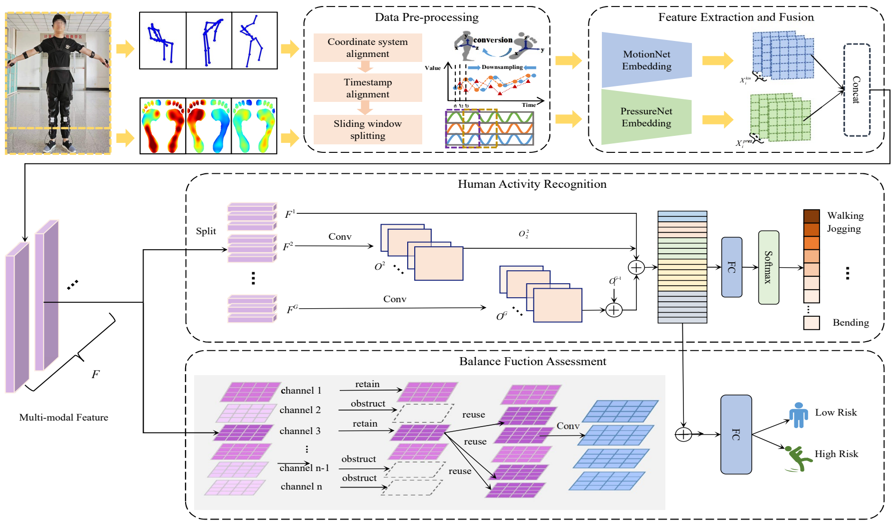

Fig. 2. M^2-Balance Overview. The proposed framework takes kinematic data and plantar pressure as inputs and extracts features using their respective feature extractors. Subsequently, activity categories are generated by the HAR module and balance states are generated by the BFA module. $\oplus$ means concatenation operation in the channel dimension.

where $\Gamma(\cdot)$ represents an integration operator that extracts stability-critical information, and $\hat{y} \in \{\text{normal}, \text{imbalance}\}$ denotes the predicted balance state. Unlike conventional classification, this formulation allows the model to jointly capture movement patterns and stability-related physiological characteristics, ensuring that assessment is grounded in the observed behavioral state.

3.2 Overview

As shown in Fig. 2, the M^2-Balance framework processes preprocessed kinematic and plantar pressure signals through feature extractors (3×3 Conv + BN + ReLU) to construct a multi-modal feature map $F \in \mathbb{R}^{H \times W \times C}$. The feature map is then fed into two parallel branches: the Human Activity Recognition and Balance Function Assessment modules. The HAR module employs hierarchical segmentation to extract multi-scale activity features F_{act} and generate the activity probability $\hat{y}_{act}$. The BFA module further reuses informative feature channels for stability analysis to produce semantic features F_{bfa}. Finally, by integrating F_{act} and F_{bfa}, the framework outputs the balance function probability $\hat{y}_{bfa}$.

3.3 Human Activity Recognition Module

Inspired by [22], we leverage the large receptive field of Hierarchical Split Convolution (HSConv) to perform multi-scale learning on multi-modal features. Given the input $F \in \mathbb{R}^{H \times W \times C}$, where H, W, and C represent the height, width, and total number of channels of F, respectively. The multi-modal feature F is evenly divided into G groups ($G = 4$), denoted as $\{F^1, F^2, \ldots, F^G\}$. For each group F^i ($i = 1, \ldots, G$), except for the first one F^1, we apply a standard convolutional operation (3×1 Conv + BN + ReLU) to obtain an intermediate feature map O^i. Each O^i is then equally split into two parts: O_1^i and O_2^i. The first part O_1^i is concatenated with the next group F^{i+1}, forming the new input for the subsequent convolution. This recursive design aims to progressively expand the model's receptive field while preserving and reusing underlying features. This process can be recursively described as:

$$O^{i+1} = \text{Conv}\left(\text{Concat}(O_1^i, F^{i+1})\right) \tag{2}$$

This recursive splitting-concatenation-convolution mechanism continues until all groups are processed. The output features from each layer are concatenated along the channel dimension to construct the multi-scale feature map F_{act}, which is then mapped through a fully connected layer to derive the activity probability distribution $\hat{y}_{act}$. This structure enables the model to progressively aggregate fine-to-coarse contextual features across groups, enhancing representation learning at multiple scales.

3.4 Balance Function Assessment Module

In order to improve the utilization efficiency of feature channels that contribute more to the balance stability analysis in the convolutional layer, inspired by [8], we design Channel Selection Convolution (CSConv). Specifically, in order to quantify the importance of each feature channel, we introduce the Expected Channel Damage Matrix (ECDM), which evaluates the contribution of a channel to the balance evaluation task by measuring the expected change in the model output before and after resetting the weight of a certain channel to zero. Given the input feature map $F \in \mathbb{R}^{H \times W \times C}$, the contribution score of each channel c is calculated as follows:

$$e_c = \frac{1}{N} \sum_{n=1}^{N} \left| f(F_n; W) - f(F_n; W_{(-c)}) \right|^2 \tag{3}$$

where $f(\cdot)$ denotes the convolution operation, N represents the total number of multi-modal feature map samples in a batch participating in the calculation, and $W(-c)$ represents the convolutional kernel with the weights of channel c zeroed out. A higher e_c indicates that the corresponding channel contains more critical information for the stability analysis.

Based on these scores, the module employs a channel gating mechanism combined with spatial shifts to achieve efficient feature reuse. The transformation for the j-th output channel is defined as:

$$\hat{F}_j = gx_j \cdot \text{Shift}(F_{x_j}, s_j) \tag{4}$$

where $x_j \in \{1, \dots, C\}$ is the index of the original input channel being reused, s_j is a learnable spatial shift offset to enhance diversity, and $g \in [0, 1]$ is a gating factor that obstructs low-contribution channels while retaining informative ones.

The selectively reused channels are concatenated along the channel dimension to synthesize the high-level semantic feature map $F_{bfa} \in \mathbb{R}^{H \times W \times C_{out}}$. To incorporate motion-specific context, F_{bfa} is fused with the multi-scale activity features F_{act} via concatenation. This joint representation is subsequently processed through a fully connected layer and a Softmax function to yield the final balance assessment probability distribution $\hat{y}_{bfa}$:

$$\hat{y}_{bfa} = \text{Softmax}(\text{FC}(\text{Concat}(F_{act}, F_{bfa}))) \tag{5}$$

To simultaneously optimize both tasks and enhance model generalization, we employ a joint loss function:

$$\mathcal{L}_{total} = \alpha \cdot \mathcal{L}_{har} + \beta \cdot \mathcal{L}_{bfa} \tag{6}$$

where α and β are weighting coefficients, and $\mathcal{L}_{har}$ and $\mathcal{L}_{bfa}$ represent the losses for the activity recognition and balance assessment tasks, respectively, with both losses defined as cross-entropy.

Table 2. Performance Comparison of M^2-Balance and State-of-the-Art Methods for Balance Function Assessment on SisFall, PDS, and MBFAD Datasets.

Method	SisFall	PDS	**MBFAD**
SelectCNN [8]	89.51 / 89.46	80.41 / 81.43	88.92 / 90.28
	88.97 / 89.53	76.59 / **80.41**	88.79 / 88.74
HC-CNN [5]	86.83 / 86.78	75.42 / 83.96	80.48 / 80.67
	86.64 / 86.80	62.78 / 50.12	80.41 / 80.41
CoS [4]	90.70 / **90.79**	84.84 / 86.85	89.32 / 89.45
	90.76 / 90.74	77.59 / 75.63	89.17 / 89.40
MFACNN [25]	89.57 / 89.62	79.56 / 64.47	81.02 / 80.90
	89.25 / 89.57	63.67 / 62.89	80.91 / 81.47
HT-AggNet [16]	90.66 / 90.69	83.72 / 86.22	88.95 / 89.86
	90.52 / 90.36	74.29 / 70.92	88.86 / 88.80
M²-Balance	**92.18** / 90.76	**87.24** / **88.33**	**92.84** / **92.88**
	91.32 / **91.89**	81.32 / 78.01	**92.87** / **92.85**

* The metrics from left to right and top to bottom are Accuracy, Precision, F1-score, and Recall, respectively. All $p < 0.05$ (McNemar's test on paired predictions from the same test set).

4 Experiments

4.1 Experimental Results on the Benchmark

To assess the effectiveness of the M^2-Balance Framework, we compare its performance with several state-of-the-art models on the SisFall, PDS, and MBFAD datasets. For all datasets, we employed a subject-independent splitting method, dividing the training and test sets in a 7:3 ratio, and used a sliding window with a length of 2 seconds and an overlap rate of 50% for preprocessing. The core hyperparameter settings were as follows: learning rate 0.0001, batch size 128, optimizer Adam, and number of training epochs 200. The results, shown in Table 2, reveal that our framework outperforms others on the MBFAD dataset, achieving the highest overall performance with 92.84% accuracy and a 92.87% F1-score, surpassing CoS and HT-AggNet by 3.52% and 3.89%, respectively. To ensure statistical reliability, we report the average accuracy across epochs where performance remains consistently high, rather than selecting the peak accuracy from a single epoch. Additionally, our framework demonstrates generalization, achieving 92.18% accuracy on SisFall and 87.24% on PDS. Importantly, all performance improvements over each baseline are statistically significant ($p < 0.05$), where McNemar's tests are conducted on paired predictions between M^2-Balance and each baseline model on the same test set.

Table 3. Performance comparison of different modal inputs of MBFAD on the M^2-Balance Framework.

Modal	HAR Task				BFA Task			
	Acc	Prec	Rec	F1	Acc	Prec	Rec	F1
Kinematic	85.93	85.44	**85.93**	85.68	88.70	88.11	88.99	88.35
Pressure	72.74	76.31	72.71	74.47	78.00	77.98	78.02	77.89
Kinematic & Pressure	**90.32**	**89.80**	85.56	**86.99**	**92.84**	**92.88**	**92.85**	**92.87**

Table 4. Performance comparison of single-task and multi-task learning on the MBFAD dataset.

Task Configuration	HAR Task				BFA Task			
	Acc	Prec	Rec	F1	Acc	Prec	Rec	F1
HAR	89.15	88.72	89.15	88.02	-	-	-	-
BFA	-	-	-	-	89.45	89.32	89.50	89.41
M^2-Balance	**90.32**	**89.80**	85.56	86.99	**92.84**	**92.88**	**92.85**	**92.87**

* "-" indicates the task was disabled in the single-task configuration.
* All $p < 0.05$ (McNemar's test on paired predictions from the same test set).

4.2 Ablation Study

To investigate the contribution of different components, we conduct ablation studies on the MBFAD dataset regarding modality and task configurations. All results are obtained using a sliding-window evaluation protocol on the test set.

As shown in Table 3, the fusion of kinematic and plantar pressure signals consistently outperforms single-modal inputs, achieving a BFA accuracy of 92.84%, compared with 88.7% for kinematic data and 78% for pressure data. Table 4 further demonstrates the effectiveness of the joint training paradigm, where M^2-Balance achieves higher HAR and BFA accuracies of 90.32% and 92.84%, compared to single-task baselines of 89.15% and 89.45%, respectively. Statistical significance for Table 4 is evaluated using McNemar's test on test-set predictions, where pairwise comparisons are performed between M^2-Balance and each single-task variant on identical test samples. All improvements are statistically significant ($p < 0.05$).

5 Conclusion

MBFAD is a multi-modal benchmark dataset that simultaneously integrates whole-body kinematic data and plantar pressure signals from 29 subjects for balance function assessment. This dataset covers static, dynamic, and reactive activities under normal and disturbed states. Based on this dataset, our propose M^2-Balance framework jointly models activity recognition and balance function assessment. Experimental results show that fusing activity context information and multi-modal features effectively improves the performance of balance function assessment tasks. However, this study still has some limitations. First, this dataset only includes young, healthy adults. In the future, we plan to further expand the sample size under stricter safety protocols to include older adults and clinical populations to validate the effectiveness of the framework in real-world clinical scenarios. Second, the current assessment is performed at the sliding window level, aiming to capture transient instability. While this method is suitable for fine-grained real-time monitoring, it differs from the individual-level assessments commonly used in clinical practice. In the future, we plan to investigate individual-level risk assessment by aggregating predictions from continuous windows into clinically interpretable scores.

Acknowledgments. This work is supported by the National Natural Science Foundation of China (62402452), the China Postdoctoral Science Foundation (2024M762992, 2025T180413), and the National Key Laboratory Independent Research Project (2025SGAQZ-QN-06, 2025SGAQZ-ZDB-05).

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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