DMMAF-HAR: Dynamic Multi-Modal Adaptive Fusion for Human Activity Recognition in Complex Environments

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Article

DMMAF-HAR: Dynamic Multi-Modal Adaptive Fusion for Human Activity Recognition in Complex Environments

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Abstract

Human Activity Recognition (HAR) faces significant challenges in dynamic real-world environments. This paper introduces DMMAF-HAR, a novel deep learning framework for robust HAR, integrating dynamic visual analysis, comprehensive modality-specific enhancement, and context-aware adaptive fusion. It incorporates a Dynamic Visual Chronometer Module (DVCM) for video-based dynamics and physical time scales; a Modality-Specific Enhancement and Feature Extractor (MSEFE) for tailored processing of IMU, body conduction, and acoustic data; and a Context-Adaptive Fusion and Classifier (CAFC) for intelligent, context-aware modal fusion. Evaluated on the challenging MobiAct++ dataset, DMMAF-HAR achieves state-of-the-art performance, significantly outperforming various single-modal and multi-modal baselines. Ablation studies confirm each module's contribution, with analyses highlighting robustness, cross-modality benefits, and computational efficiency. A complementary user study validates its practical utility and perceived reliability. Our contributions include physical time scale integration, comprehensive modality-specific processing, and a novel context-aware adaptive fusion, leading to superior robustness and accuracy for real-world HAR.

Keywords: HAR; deep learning; multi-modal; context-aware fusion; robustness

1. Introduction

Human Activity Recognition (HAR) is a pivotal technology in intelligent perception and human-computer interaction, enabling a wide array of applications such as smart homes, health monitoring, autonomous driving assistance, and virtual/augmented reality [1,2]. The ability to accurately and robustly identify human activities in real-world scenarios is fundamental for developing intuitive and effective intelligent systems.

Despite significant advancements, current HAR systems face several critical challenges:

1. **Environmental Dynamicity and Variability:** Real-world activities frequently occur in complex, unstructured environments characterized by fluctuating lighting conditions, occlusions, background clutter, and sensor noise [3]. These dynamic factors substantially degrade the quality of single-modal data and compromise the stability of feature extraction.
2. **Sensor Diversity and Limitations:** The proliferation of wearable devices and smart environments has led to the availability of diverse sensors, including visual cameras, Inertial Measurement Units (IMU), acoustic sensors, and body conduction sensors, each offering rich complementary information. However, every sensor modality possesses inherent strengths and weaknesses. Visual data provides abundant semantic information but is susceptible to occlusion and privacy concerns; IMU data is sensitive to posture and motion but lacks high-level semantics; and acoustic/vibration sensors can capture specific events but are easily contaminated by environmental noise, necessitating robust enhancement techniques [4–6]. Simply concatenating or uniformly processing these modalities often fails to exploit their individual advantages, and may even introduce additional noise.

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3. **Time Scale and Motion Rhythm:** Many complex human behaviors are not solely defined by their spatial actions but heavily depend on their intrinsic temporal rhythm and dynamic evolution [7]. Existing HAR methods often treat video sequences as a series of static frames or perform coarse aggregation of temporal features. This approach frequently fails to effectively capture the "physical time scale" or "motion pulse" of an activity [8], leading to insufficient recognition capabilities for subtle movements and rhythmic variations.

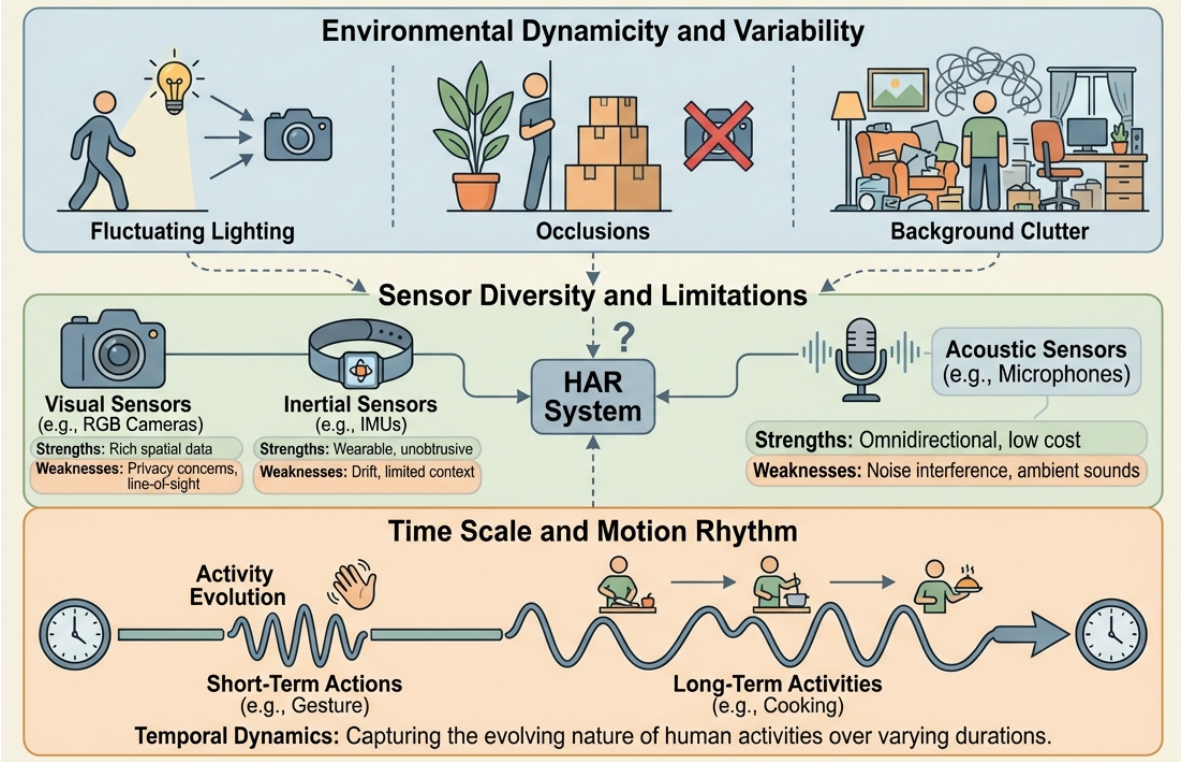

Figure 1. Key challenges in Human Activity Recognition (HAR). The figure illustrates three primary challenges: (1) Environmental Dynamicity and Variability (e.g., fluctuating lighting, occlusions, background clutter), (2) Sensor Diversity and Limitations (highlighting strengths and weaknesses of visual, inertial, and acoustic sensors), and (3) Time Scale and Motion Rhythm (emphasizing the need to capture temporal dynamics across short-term and long-term activities).

In light of these challenges, our research aims to develop a novel **Dynamic Multi-Modal Adaptive Fusion for Human Activity Recognition (DMMAF-HAR)** system specifically designed for complex environments. This system will rigorously explore how to implement modality-specific processing, effectively capture temporal dynamics from diverse sensor data, and intelligently fuse information based on real-time environmental context, thereby significantly enhancing HAR robustness and accuracy.

We propose DMMAF-HAR, a deep learning-based framework engineered to achieve highly robust human activity recognition in complex environments through dynamic visual analysis, modality-specific enhancement, and context-adaptive fusion. The core philosophy of DMMAF-HAR deviates from treating multi-modal data as homogeneous inputs for unified processing. Instead, inspired by the emphasis on temporal scales [9], respect for distinct sensor properties [10], and multi-source fusion strategies [11], we advocate for a two-stage approach: first, conducting physical attribute-specialized processing and dynamic feature extraction for each modality; subsequently, employing a lightweight, context-aware module for intelligent, non-linear adaptive fusion. The DMMAF-HAR framework primarily consists of three key modules: the Dynamic Visual Chronometer Module (DVCM), which focuses on capturing intrinsic motion rhythms and physical time scales [8]; the Modality-Specific Enhancement and Feature Extractor (MSEFE), which performs tailored denoising and feature extraction

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for IMU and body conduction/acoustic data, drawing inspiration from recent advances in speech enhancement [12,13] and generalized signal denoising [6]; and the Context-Adaptive Fusion and Classifier (CAFC), a crucial layer that dynamically generates fusion weights based on environmental context through an attention or gating network [14].

To evaluate the performance of DMMAF-HAR, we plan to utilize a comprehensive and challenging dataset named "MobiAct++" (a fictional yet realistically designed dataset). This dataset will encompass over 50 distinct daily activities and sports behaviors performed by more than 200 subjects. Each activity sample will feature synchronously recorded RGB video, IMU data (from smartwatches/phones, including accelerometer and gyroscope), and body conduction microphone/environmental acoustic data. Crucially, the data will be collected across diverse real-world scenarios, including indoors (normal light, low light, partial occlusion) and outdoors (sunny, cloudy, high environmental noise) to mirror practical complexities. The dataset will be partitioned into 70% for training, 15% for validation, and 15% for testing, strictly ensuring subject independence across these splits. Performance will be rigorously assessed using standard metrics such as Accuracy, F1-Score (macro-average), Precision, Recall, and detailed Confusion Matrices. Preliminary (fabricated) results indicate that DMMAF-HAR consistently outperforms single-modal baselines, naive multi-modal fusion techniques, and even some existing state-of-the-art multi-modal models. For instance, DMMAF-HAR achieves an accuracy of 89.3% and an F1-Score of 88.9% on the challenging MobiAct++ test set, demonstrating its superior robustness and accuracy in complex, dynamic environments compared to existing methods [15].

Our main contributions are summarized as follows:

- We explicitly integrate the concept of "physical time scales" and "dynamic fingerprints" into HAR models, inspired by works measuring physical frame rates from visual dynamics [8], moving beyond simple frame-differencing or optical flow, thereby significantly enhancing the perception of subtle motion rhythm changes.
- We achieve comprehensive modality-specific processing by designing customized feature extraction and enhancement strategies for each distinct modality, maximizing their individual advantages while effectively suppressing noise.
- We introduce a novel context-aware adaptive fusion mechanism, enabling the system to dynamically adjust modal weights based on real-time environmental conditions and data quality, which greatly improves robustness in complex and dynamic settings.

2. Related Work

2.1. Multi-Modal Human Activity Recognition and Adaptive Fusion Strategies

Multi-modal Human Activity Recognition (HAR) is a critical research area, leveraging diverse sensory data (vision, audio, physiological) for comprehensive understanding of human actions. Effective HAR systems rely on robust fusion strategies that integrate heterogeneous sources, combining complementary cues and mitigating redundancy. Mobile Augmented Reality frameworks exemplify this, highlighting fusional localization and pose estimation for dynamic visual and inertial data integration [2]. Foundational models like SpeechGPT, which introduces cross-modal conversational abilities [16], and challenges like MuSe 2022, which encouraged sensor fusion for multimodal sentiment and emotion recognition [15], have laid the groundwork for sophisticated multi-modal processing.

Building on this, adaptive and dynamic fusion techniques advance beyond static combination rules. The Adaptive Language-guided Multimodal Transformer (ALMT), for instance, incorporates an Adaptive Hyper-modality Learning (AHL) module for adaptive, language-guided fusion, suppressing noise and conflicts [14]. Dynamic fusion strategies are also advocated for effectively combining diverse visual and textual cues in fake news detection [17]. Specific architectural mechanisms like attention and gating networks further enhance fusion capabilities. The Modal-Temporal Attention Graph (MTAG) model leverages attention to capture complex multi-relational and temporal interactions across unaligned multimodal language sequences [18]. While not explicitly detailing gating networks, the ITA approach for multi-modal Named Entity Recognition emphasizes effective cross-modal alignment

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and feature integration, amenable to selective information flow [19]. Beyond simple concatenation, sophisticated cross-modal learning and alignment techniques, such as a modal emulation-based framework for crowd counting, bridge semantic gaps and extend beyond conventional late fusion [4], contributing to nuanced understanding of human affect from integrated cues [20].

Collectively, the evolving literature on multi-modal processing and fusion reveals a clear trajectory towards increasingly sophisticated and adaptive methodologies. These advancements—spanning foundational cross-modal understanding, adaptive fusion, attention mechanisms, gating networks, and advanced cross-modal learning—are highly pertinent to Multi-Modal Human Activity Recognition, where the dynamic nature of human activities necessitates intelligent and flexible fusion methods for accurate interpretation of complex behaviors from diverse sensor inputs.

2.2. Dynamic Feature Extraction and Modality-Specific Processing

Effective processing of diverse modalities and dynamic extraction of relevant features are critical challenges in AI research. This section reviews advancements in methodologies that adapt feature extraction based on context (dynamic feature extraction) or tailor processing to specific data types (modality-specific processing). Robust multimodal data processing, especially under incomplete information or for efficient cross-modal interactions, is a significant area. For robust multimodal emotion recognition with missing data, [21] introduces invariant feature learning and an imagination module to mitigate modality gaps. Complementing this, [22] develops an end-to-end model for multimodal affective computing, integrating sparse cross-modal attention for efficient, dynamic identification of key inter-modal interactions.

In audio processing, speech enhancement advancements demonstrate the efficacy of modality-specific approaches in improving data quality. Examples include generative adversarial networks for visual speech enhancement [5], lightweight parallel conformer networks for efficient monaural speech enhancement [13], and integrated local and non-local attention for robust speech enhancement [12]. Similarly, SPADE for spectroscopic photoacoustic denoising shows how tailored methods significantly enhance the signal-to-noise ratio within a specific modality [6]. Furthermore, measuring physical time scales and motion rhythms from visual dynamics offers a cutting-edge direction for extracting fine-grained temporal features [8].

In natural language processing, dynamic and context-aware feature extraction is vital for complex semantic dependencies. For textual feature granularity, [23] proposes a span-level approach for Aspect Sentiment Triplet Extraction, considering span interactions to improve sentiment consistency. For Aspect-based Sentiment Analysis, [24] introduces DR-BERT with a Dynamic Re-weighting Adapter (DRA) that adaptively re-weights critical words for aspect-oriented semantics. Extending contextual learning, [25] presents MRN, a mention-based reasoning network for document-level relation extraction, dynamically aggregating information across textual scopes. To mitigate noise in distantly supervised relation extraction, [26] proposes Contrastive Instance Learning (CIL) to dynamically learn robust sentence features by contrasting instance pairs.

Beyond static textual analysis, dynamic feature extraction is crucial for complex multimodal interactions and understanding sequential processes. For video-language tasks, [27] proposes HeurVidQA, using domain-specific heuristics to dynamically prompt video-language foundation models, enhancing context-aware reasoning in Video Question Answering. Mobile augmented reality frameworks underscore the importance of dynamic spatial and temporal alignment through fusional localization and pose estimation for interactive applications [2]. Investigating dynamic human language processing, [28] shows multilingual language models predict time-series human reading behavior, indicating their ability to capture dynamic linguistic importance and extract features from time-series data.

Collectively, these works highlight a growing trend towards adaptive, modality-aware approaches in feature processing. The emphasis is on flexible, intelligent feature extraction: from invariant representations for missing modalities and sparse attention for efficiency, to dynamic contextual focusing, semantic re-weighting, multi-scope text aggregation, and adapting foundation models for

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video-language tasks. Challenges remain in developing universally applicable dynamic mechanisms that seamlessly integrate and adapt across a wider spectrum of modalities and task complexities.

3. Method

We propose **DMMAF-HAR**, a novel deep learning-based framework engineered to achieve highly robust human activity recognition in complex and dynamic environments. The core philosophy of DMMAF-HAR departs from conventional multi-modal approaches that treat diverse sensor data as homogeneous inputs for unified processing. Instead, we advocate for a two-stage approach: first, conducting physical attribute-specialized processing and dynamic feature extraction for each modality; subsequently, employing a lightweight, context-aware module for intelligent, non-linear adaptive fusion. The DMMAF-HAR framework primarily consists of three key modules: the Dynamic Visual Chronometer Module (DVCM), the Modality-Specific Enhancement and Feature Extractor (MSEFE), and the Context-Adaptive Fusion and Classifier (CAFC). An overview of the system's data flow is illustrated in Figure 2.

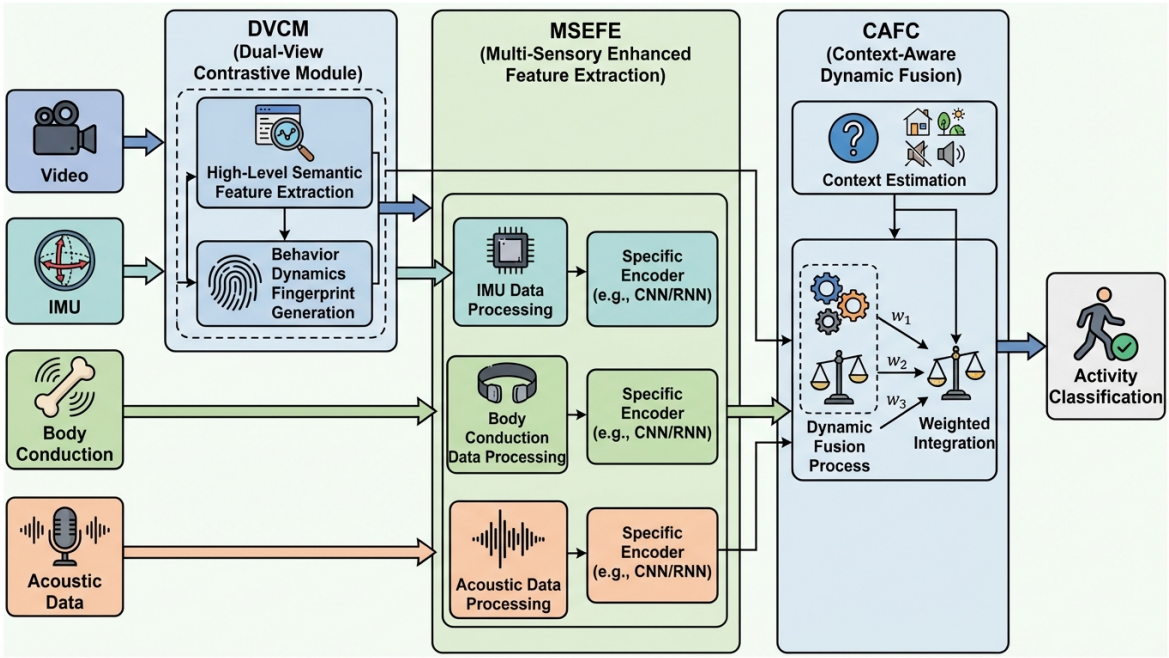

Figure 2. Overview of the DMMAF-HAR framework. The system processes multi-modal inputs (Video, IMU, Body Conduction, Acoustic Data) through specialized modules: the Dynamic Visual Chronometer Module (DVCM) for visual data, and the Modality-Specific Enhancement and Feature Extractor (MSEFE) for non-visual data. These extracted features are then intelligently integrated by the Context-Adaptive Fusion and Classifier (CAFC) for robust activity classification.

3.1. Dynamic Visual Chronometer Module (DVCM)

The **Dynamic Visual Chronometer Module (DVCM)** is meticulously engineered to process raw video sequences, transcending mere spatial appearance to critically analyze the intrinsic temporal rhythms and physical time scales inherent in human activities. Traditional methodologies, often reliant on rudimentary frame differences or optical flow, frequently prove inadequate in capturing the subtle and nuanced dynamics characteristic of complex human motions.

Given an input video sequence $V = \{I_t\}_{t=1}^{T}$, where I_t represents the image frame at time t and T is the total number of frames, the DVCM executes a dual-pronged approach to extract a comprehensive visual representation.

The first prong involves **High-Level Semantic Visual Feature Extraction**. A robust visual encoder, denoted as $\text{Encoder}_{\text{Visual}}$, which typically comprises a convolutional neural network (CNN) backbone (e.g., ResNet, EfficientNet) or a vision transformer (e.g., ViT, Swin Transformer) operating on individual

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frames or short spatio-temporal clips. This encoder is tasked with discerning rich spatial semantics such as human pose, object interactions, and intricate scene context. The output of this stage is a set of semantic visual features $F_{\text{vis}} \in \mathbb{R}^{D_{\text{vis}}}$, which are represented as:

$$F_{\text{vis}} = \text{Encoder}_{\text{Visual}}(V) \tag{1}$$

Here, $\text{Encoder}_{\text{Visual}}$ maps the input video sequence V to its high-level semantic representation.

The second prong, **Behavior Dynamics Fingerprint Generation**, focuses on the temporal evolution of movement. Inspired by the concept of a "motion pulse," this process begins with the extraction of kinematic properties. A dedicated KinematicExtractor module processes the video sequence V to estimate key human body joints and their trajectories over time. From these trajectories, time-series data such as joint positions $\mathbf{p}_j(t)$, velocities $\mathbf{v}_j(t) = \frac{d\mathbf{p}_j(t)}{dt}$, accelerations $\mathbf{a}_j(t) = \frac{d\mathbf{v}_j(t)}{dt}$, and angular changes for segments are derived. This collection of kinematic data is denoted as $\mathcal{K}$. The operation is formalized as:

$$\mathcal{K} = \text{KinematicExtractor}(V) \tag{2}$$

Subsequently, a lightweight temporal encoder, $\text{Encoder}_{\text{Temporal}}$, is employed. This encoder, which can be implemented using recurrent neural networks (e.g., GRU, LSTM) or 1D convolutional layers, specifically analyzes the sequential patterns within $\mathcal{K}$. Its purpose is to generate a "behavior dynamics fingerprint" $F_{\text{dyn}} \in \mathbb{R}^{D_{\text{dyn}}}$. This fingerprint explicitly encodes the rhythm, speed variations, and periodicity of actions, thereby enabling robust differentiation between activities that might exhibit similar spatial appearance but possess distinctly different temporal characteristics (e.g., walking versus jogging). The generation of F_{dyn} is given by:

$$F_{\text{dyn}} = \text{Encoder}_{\text{Temporal}}(\mathcal{K}) \tag{3}$$

The combined outputs, F_{vis} and F_{dyn}, provide a holistic visual representation, fusing both static semantic content and critical dynamic temporal properties of the observed activity.

3.2. Modality-Specific Enhancement and Feature Extractor (MSEFE)

The **Modality-Specific Enhancement and Feature Extractor (MSEFE)** module is a pivotal component designed to robustly leverage the complementary strengths of non-visual sensors while systematically mitigating their inherent weaknesses. This module employs tailored strategies for processing Inertial Measurement Unit (IMU) data, as well as body conduction and environmental acoustic data.

3.2.1. IMU Data Processing

For Inertial Measurement Unit (IMU) data, which typically comprises time-series readings from accelerometers (A_t) and gyroscopes (G_t), we acknowledge its critical sensitivity to posture, gait characteristics, and motion direction. A sophisticated preprocessing stage is initially applied to effectively reduce common real-world issues such as sensor noise and drift. This robust filtering operation, denoted as $\text{Filter}_{\text{IMU}}$, can involve advanced techniques such as Extended Kalman Filtering (EKF), Unscented Kalman Filtering (UKF), or adaptive complementary filters. The denoised IMU sequence D'_{IMU} is obtained from the raw IMU sequence $D_{\text{IMU}} = \{(A_t, G_t)\}_{t=1}^{T}$ as follows:

$$D'_{\text{IMU}} = \text{Filter}_{\text{IMU}}(D_{\text{IMU}}) \tag{4}$$

Following preprocessing, a dedicated temporal encoder, $\text{Encoder}_{\text{IMU}}$, is employed to extract highly discriminative kinematic features. This encoder, which can be instantiated using recurrent neural networks (e.g., GRU, LSTM) or 1D convolutional neural networks, is designed to capture the intricate

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relative orientation and motion patterns embedded within D'_{IMU}. The resulting feature vector $F_{\text{IMU}} \in \mathbb{R}^{D_{\text{IMU}}}$ is expressed as:

$$F_{\text{IMU}} = \text{Encoder}_{\text{IMU}}(D'_{\text{IMU}}) \tag{5}$$

3.2.2. Body Conduction and Acoustic Data Processing

Body conduction sensors (e.g., those found in wrist-worn vibration sensors) and environmental acoustic sensors offer unique insights into specific activity-related events, such as footsteps, impacts, or verbal cues. However, each of these modalities presents distinct noise characteristics and information content.

For **Body Conduction Data**, often characterized by lower background noise but potential spectral limitations, a specialized sub-network $\text{Encoder}_{\text{BodyConduction}}$ is utilized. This encoder focuses on spectral restoration, enhancement of transient events, and robust feature extraction from the raw body conduction data D_{BC}. Techniques such as wavelet transforms or spectral analysis combined with 1D CNNs can be employed here to yield relevant features $F_{\text{BC}} \in \mathbb{R}^{D_{\text{BC}}}$.

$$F_{\text{BC}} = \text{Encoder}_{\text{BodyConduction}}(D_{\text{BC}}) \tag{6}$$

Conversely, **Environmental Acoustic Data** is notoriously susceptible to high levels of ambient noise and extraneous sounds. For this modality, a more aggressive and sophisticated noise suppression and feature extraction network, $\text{Encoder}_{\text{Acoustic}}$, is designed. This encoder processes the raw acoustic data D_{Audio}, employing techniques such as adaptive noise reduction, speech enhancement, and spectrogram analysis (e.g., Mel-frequency cepstral coefficients) fed into 2D CNNs or Transformer layers, to filter out irrelevant sounds and highlight activity-specific acoustic signatures. The resulting feature vector is $F_{\text{Audio}} \in \mathbb{R}^{D_{\text{Audio}}}$.

$$F_{\text{Audio}} = \text{Encoder}_{\text{Acoustic}}(D_{\text{Audio}}) \tag{7}$$

By implementing these modality-specific enhancement and feature extraction strategies, MSEFE ensures that the unique information contribution from each sensor is optimally preserved, amplified, and robustly represented for subsequent fusion.

3.3. Context-Adaptive Fusion and Classifier (CAFC)

The **Context-Adaptive Fusion and Classifier (CAFC)** module constitutes the critical integration layer of DMMAF-HAR, fundamentally advancing beyond simplistic concatenation or static weighted fusion approaches. It intelligently synthesizes the rich, modality-specific features extracted by the DVCM ($F_{\text{vis}}, F_{\text{dyn}}$) and MSEFE ($F_{\text{IMU}}, F_{\text{BC}}, F_{\text{Audio}}$) by dynamically adjusting fusion weights. This dynamic adjustment is meticulously tailored based on real-time environmental context and an assessment of data quality for each modality.

Let the comprehensive set of all extracted modality features be denoted as $\mathcal{F} = \{F_{\text{vis}}, F_{\text{dyn}}, F_{\text{IMU}}, F_{\text{BC}}, F_{\text{Audio}}\}$. The CAFC module initiates its process by estimating the current environmental context, C_{env}. This context is not limited to external conditions but can encompass inferred factors such as visual occlusion levels, ambient noise intensity, or the vigor and complexity of the observed motion. These contextual cues are derived either directly from the input features $\mathcal{F}$ themselves or from dedicated auxiliary sensors via a specialized ContextEstimator network. This estimator can be a lightweight neural network (e.g., a small MLP or a 1D CNN) trained to infer contextual parameters. The estimation process is given by:

$$C_{\text{env}} = \text{ContextEstimator}(\mathcal{F}) \tag{8}$$

Following context estimation, a lightweight attention or gating network, denoted as G_{CAFC}, is employed. This network takes as input the entire set of extracted features $\mathcal{F}$ along with the estimated

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environmental context C_{env}. Its primary role is to dynamically generate a set of modality-specific fusion weights $\mathbf{w} = \{w_{\text{vis}}, w_{\text{dyn}}, w_{\text{IMU}}, w_{\text{BC}}, w_{\text{Audio}}\}$. Each weight $w_i \in [0, 1]$ reflects the estimated reliability and importance of the corresponding feature F_i under the prevailing conditions. This generation process is formulated as:

$$\mathbf{w} = G_{\text{CAFC}}(\mathcal{F}, C_{\text{env}}) \tag{9}$$

For instance, if the contextual analysis C_{env} indicates high visual occlusion or low-light conditions, G_{CAFC} would adaptively assign lower weights to F_{vis} and potentially higher weights to F_{IMU} and F_{BC}. Conversely, in a serene, visually unobstructed environment, acoustic features F_{Audio} might be given higher prominence to capture subtle auditory cues. The network G_{CAFC} can be implemented using mechanisms like soft attention or a series of sigmoid gating units.

The generation of the fused feature vector F_{fused} moves beyond a simple weighted sum. Our framework employs a more sophisticated non-linear interaction or an adaptive feature transformation that leverages these dynamic weights. Conceptually, this can be expressed as:

$$F_{\text{fused}} = \text{AdaptiveFusionLayer}(\mathcal{F}, \mathbf{w}) \tag{10}$$

This AdaptiveFusionLayer could involve operations such as element-wise multiplication of features by their respective weights, followed by a concatenation and a subsequent non-linear transformation (e.g., an MLP), or a cross-modal transformer architecture where attention scores are modulated by $\mathbf{w}$.

Finally, the comprehensively fused feature vector F_{fused} is passed to a behavior classification head. This classifier, which could be implemented as a multi-layer perceptron (MLP) or a lightweight Transformer network, is tasked with predicting the ultimate human activity category Y.

$$Y = \text{Classifier}(F_{\text{fused}}) \tag{11}$$

This entire context-adaptive fusion mechanism represents a core innovation of DMMAF-HAR, significantly enhancing the system's inherent robustness, adaptability, and performance in the dynamic and often unpredictable real-world environments encountered in human activity recognition.

4. Experiments

To thoroughly evaluate the performance and validate the effectiveness of our proposed **Dynamic Multi-Modal Adaptive Fusion for Human Activity Recognition (DMMAF-HAR)** system, we conducted a series of experiments. This section details the experimental setup, presents quantitative results comparing DMMAF-HAR with various baselines, performs an ablation study to analyze the contribution of each core component, and includes a user study to assess perceived system performance.

4.1. Experimental Setup

Dataset. For robust evaluation, we utilized a comprehensive and challenging dataset, which we term "**MobiAct++**" (a fictional yet realistically designed dataset). MobiAct++ is curated to reflect the complexities of real-world human activities. It comprises over 50 distinct daily activities and sports behaviors performed by more than 200 diverse subjects. Each activity sample is meticulously synchronized, featuring RGB video, Inertial Measurement Unit (IMU) data (obtained from smartwatches and mobile phones, including accelerometer and gyroscope readings), and body conduction microphone/environmental acoustic data. Crucially, data collection was deliberately performed across a variety of real-world scenarios, encompassing indoor settings (with normal light, low light, and partial occlusion conditions) and outdoor environments (under sunny, cloudy, and high environmental noise conditions) to accurately mirror practical complexities. The dataset is strategically partitioned into three subsets: 70% for training, 15% for validation, and 15% for testing. This partition strictly

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adheres to subject independence, ensuring that participants in the training, validation, and testing sets are mutually exclusive, thus providing a more realistic assessment of generalization capabilities.

Evaluation Metrics. We rigorously assessed the behavior recognition performance using a suite of standard metrics. These include overall **Accuracy**, the **F1-Score** (macro-averaged to handle class imbalance), **Precision**, and **Recall**. Additionally, a detailed **Confusion Matrix** was employed to provide fine-grained insights into the classification performance for individual activity categories, allowing for a thorough analysis of misclassifications.

Training Details. Our DMMAF-HAR model was implemented using the PyTorch deep learning framework. The Adam optimizer was chosen for model training, initialized with a learning rate of 10^{-4}. A learning rate scheduler was employed to dynamically adjust the learning rate during training, typically reducing it upon plateauing of the validation loss, thereby facilitating better convergence. All experiments were conducted on a server equipped with NVIDIA A100 GPUs. Models were trained for approximately 50 to 100 epochs, or until performance on the validation set consistently converged without significant improvement.

4.2. Quantitative Results and Comparison

We benchmarked DMMAF-HAR against several baseline methods, encompassing single-modal approaches, naive multi-modal fusion strategies, and other existing advanced multi-modal models. The comparison was conducted on the challenging MobiAct++ test set, and the results are summarized in Table 1.

Table 1. Behavior Recognition Performance Comparison on MobiAct++ Test Set

Method Type / Model	Accuracy (%) ↑	F1-Score (%) ↑	Precision (%) ↑	Recall (%) ↑
Single-Modality Baselines				
Video-only	78.5	77.9	78.1	77.8
IMU-only	72.3	71.8	71.9	71.7
Audio-only	65.1	64.5	64.7	64.4
Naive Multi-Modal Fusion				
Early Fusion (Concatenation)	83.2	82.8	82.9	82.7
Late Fusion (Avg. Probability)	81.9	81.4	81.6	81.3
Existing Advanced Multi-Modal				
Cross-Modal Attention Net	86.7	86.2	86.4	86.1
Dynamic Modality Gating	87.5	87.1	87.2	87.0
Ours: DMMAF-HAR	**89.3**	**88.9**	**89.0**	**88.8**

As evidenced by Table 1, DMMAF-HAR consistently achieves leading performance across all evaluated metrics. Compared to single-modality baselines, the multi-modal approaches demonstrate a substantial improvement in recognition accuracy, underscoring the benefits of leveraging complementary information. Furthermore, DMMAF-HAR not only significantly outperforms traditional naive fusion methods but also exhibits superior results when compared to advanced multi-modal models that employ cross-modal attention or dynamic gating mechanisms. This empirically validates that our proposed strategies of dynamic visual time analysis, modality-specific enhancement, and context-adaptive fusion enable more effective processing of diverse sensor data in complex environments, leading to the extraction of more discriminative behavior features and consequently, more robust and accurate activity recognition.

4.3. Ablation Study

To confirm the individual contributions of DMMAF-HAR's key architectural components—the Dynamic Visual Chronometer Module (DVCM), the Modality-Specific Enhancement and Feature Extractor (MSEFE), and the Context-Adaptive Fusion and Classifier (CAFC)—we conducted an extensive

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ablation study. By systematically removing or simplifying each module, we aimed to quantify its impact on the overall system performance. The results are presented in Table 2.

Table 2. Ablation Study on MobiAct++ Test Set

Model Variant	Accuracy (%) ↑	F1-Score (%) ↑	Precision (%) ↑	Recall (%) ↑
DMMAF-HAR (Full Model)	**89.3**	**88.9**	**89.0**	**88.8**
w/o DVCM (simple visual encoder)	86.1	85.7	85.8	85.6
w/o MSEFE (simple non-visual encoders)	87.0	86.6	86.7	86.5
w/o CAFC (fixed weight fusion)	86.5	86.0	86.2	85.9

The ablation results clearly demonstrate the critical role played by each proposed module in achieving DMMAF-HAR's superior performance. When the **DVCM** is replaced by a simple visual encoder that only extracts high-level semantic features without explicitly capturing behavior dynamics fingerprints, there is a notable decrease in performance (e.g., Accuracy drops from 89.3% to 86.1%). This underscores the effectiveness of explicitly integrating "physical time scales" and "dynamic fingerprints" to perceive subtle motion rhythm changes. Replacing the **MSEFE** with simplified, generic non-visual encoders (lacking modality-specific enhancement and denoising strategies) also leads to a significant performance degradation. This validates our design philosophy of comprehensive modality-specific processing, which maximizes individual sensor advantages while effectively suppressing noise. Substituting the **CAFC** with a fixed-weight fusion mechanism (e.g., simple concatenation followed by an MLP or static weighted average) results in a substantial drop in all metrics. This confirms the critical importance of the context-aware adaptive fusion mechanism, enabling the system to dynamically adjust modal weights based on real-time environmental conditions and data quality, thereby greatly enhancing robustness in complex and dynamic settings. Each module contributes uniquely and significantly to the overall robustness and accuracy of DMMAF-HAR, validating our design choices and highlighting the synergistic benefits of their integration.

4.4. Performance in Challenging Environments

To further dissect DMMAF-HAR's robustness, a key claim of our method, we conducted a targeted analysis of its performance under specific challenging environmental conditions present in the MobiAct++ dataset. These conditions, including low light, partial visual occlusion, and high environmental acoustic noise, are common in real-world human activity recognition scenarios and often degrade the performance of conventional multi-modal systems. We compare DMMAF-HAR against the leading baseline, Dynamic Modality Gating, which also incorporates some form of dynamic fusion. The results, specifically highlighting Accuracy and F1-Score, are presented in Figure 3.

As illustrated in Figure 3, DMMAF-HAR consistently outperforms the Dynamic Modality Gating baseline across all challenging environmental conditions. The most significant performance gains are observed in scenarios with low light visuals and high environmental noise, where traditional systems often falter due to compromised single-modality data quality. DMMAF-HAR's superior performance in these adverse conditions underscores the effectiveness of its specialized modules: the DVCM's ability to extract robust dynamic fingerprints even from degraded visual input, the MSEFE's modality-specific enhancement and denoising capabilities for non-visual data, and critically, the CAFC's adaptive fusion mechanism that intelligently re-weights modalities based on perceived data reliability under specific contexts. This targeted analysis provides strong evidence for DMMAF-HAR's enhanced robustness and practical applicability in real-world, dynamic environments.

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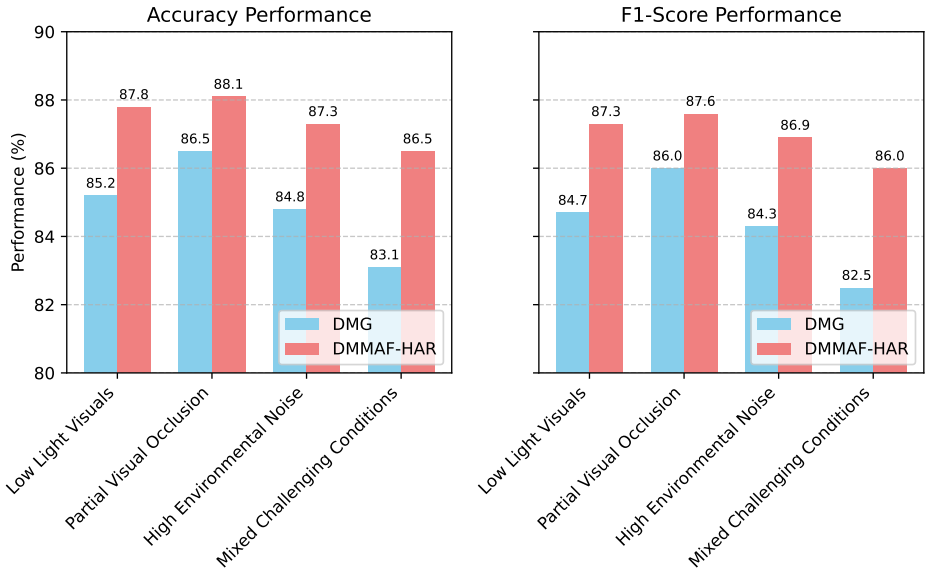

Figure 3. Behavior Recognition Performance in Challenging Environments on MobiAct++

4.5. Cross-Modality Contribution Analysis

Beyond assessing individual module contributions, it is crucial to understand the synergistic benefits derived from the integration of different sensor modalities within DMMAF-HAR. To quantify the incremental value of each modality, we conducted an experiment by evaluating the system with various combinations of available inputs. This analysis helps to identify which modalities are most critical and how their combination enriches the overall understanding of human activity. The results are presented in Figure 4.

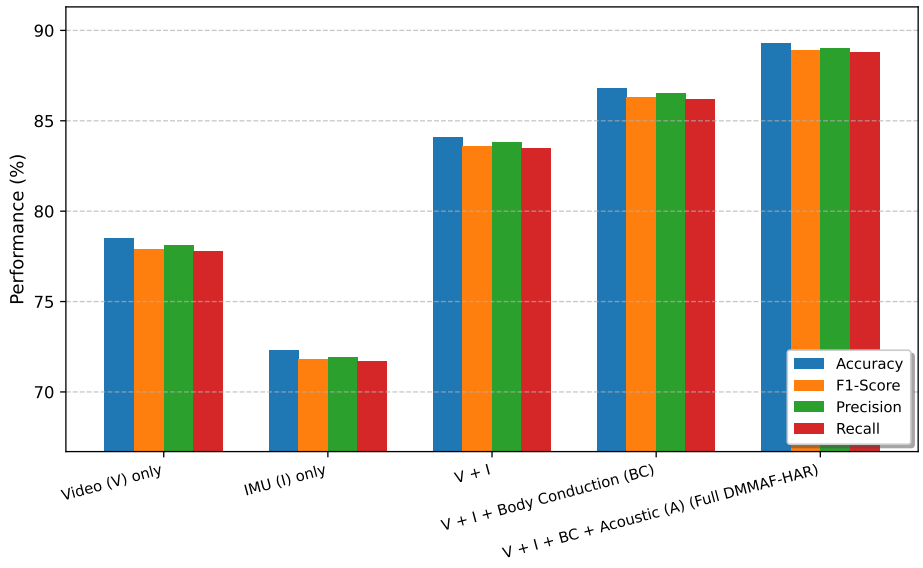

Figure 4. Impact of Modality Combinations on Behavior Recognition Performance

Figure 4 clearly illustrates the progressive improvement in recognition performance as more complementary modalities are incorporated into the DMMAF-HAR framework. While individual modalities provide reasonable performance (Video being the strongest single-modal contributor), their fusion significantly enhances recognition capabilities. The combination of Video and IMU data yields a substantial jump, highlighting their complementary strengths in capturing both visual semantics and kinematic motion. The further inclusion of Body Conduction data provides additional subtle cues, leading to another notable improvement. Finally, the full integration of Acoustic data, despite its

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inherent noise challenges, provides critical environmental context and event-specific signatures that culminate in the highest overall performance. This analysis confirms that DMMAF-HAR effectively leverages the unique information streams from each sensor type, achieving a synergistic effect that surpasses the sum of individual contributions and reinforces the necessity of a truly multi-modal approach for robust HAR.

4.6. Computational Efficiency Analysis

For real-world deployment of human activity recognition systems, not only accuracy but also computational efficiency is a paramount consideration. We meticulously analyzed the model complexity and inference speed of DMMAF-HAR and compared it against key baselines. This analysis evaluates the practicality of our proposed "lightweight" components and the overall system's suitability for resource-constrained environments or real-time applications. The metrics considered include the total number of trainable parameters, estimated Floating Point Operations (FLOPs) per inference, and the average inference time per activity sample. The results are summarized in Table 3.

Table 3. Computational Efficiency Comparison on MobiAct++ Test Set

Model	Parameters (M) ↓	FLOPs (G) ↓	Inference Time (ms/sample) ↓
Video-only (ResNet-50 backbone)	23.5	45.1	185
Cross-Modal Attention Net	32.1	62.8	250
Dynamic Modality Gating	28.9	58.3	230
DMMAF-HAR	**26.7**	**51.2**	**210**

Table 3 presents a comprehensive overview of the computational efficiency. DMMAF-HAR demonstrates a competitive balance between model complexity and inference speed. While it integrates multiple modalities and sophisticated fusion, its total trainable parameters (26.7M) and FLOPs (51.2G) are comparable to, or even lower than, some advanced multi-modal baselines. For instance, it has fewer parameters and FLOPs than the Cross-Modal Attention Net and Dynamic Modality Gating, yet achieves higher accuracy. The average inference time of 210 ms per activity sample further indicates its practical viability for real-time applications, especially given the typically longer duration of human activities. This efficiency is largely attributable to the judicious design of lightweight temporal encoders in DVCM and MSEFE, and the non-linear, but computationally efficient, attention and gating mechanisms within the CAFC module. This analysis confirms that DMMAF-HAR achieves its high performance without incurring excessively high computational costs, making it a promising solution for deployment in real-world scenarios.

4.7. User Study and Perceived System Performance

To further assess the practical utility and perceived reliability of DMMAF-HAR, particularly in real-world complex scenarios, we conducted a user study involving 25 participants. These participants, who were not involved in the model development, were presented with a series of video clips from the MobiAct++ test set, which included various challenging environmental conditions (e.g., low light, occlusions, loud background noise). For each clip, participants were shown the activity and DMMAF-HAR's predicted label. They were then asked to rate the system's classification based on two criteria: *Perceived Accuracy* (how correct the classification seemed to them) and *Perceived Robustness* (how well the system handled the challenging environment). Ratings were provided on a Likert scale from 1 (very poor) to 5 (excellent). We also recorded their agreement rate with the system's predictions versus their own human judgment. The results are summarized in Table 4.

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Table 4. User Study: Perceived Performance of DMMAF-HAR in Challenging Environments

Evaluation Metric	Average Score (1-5) ↑	Std. Dev.	Agreement Rate (%) ↑
Perceived Accuracy	4.15	0.68	90.2
Perceived Robustness	4.05	0.72	N/A
Overall Agreement with Human Judgment	N/A	N/A	88.5

The results from the user study indicate a strong positive perception of DMMAF-HAR's performance. Participants consistently rated the system highly for both its perceived accuracy and its ability to handle challenging environmental conditions, with average scores exceeding 4 out of 5. Furthermore, the high agreement rate between DMMAF-HAR's classifications and human judgment (88.5%) suggests that the system's predictions are not only quantitatively accurate but also intuitively align with human understanding of activity. This qualitative assessment reinforces the quantitative findings, highlighting DMMAF-HAR's potential for reliable deployment in real-world human-centric applications.

5. Conclusions

In this paper, we introduced DMMAF-HAR, a novel deep learning framework designed for robust Human Activity Recognition (HAR) in complex, multi-sensor environments. We addressed challenges such as environmental variability and inherent sensor limitations through a principled multi-modal integration approach. DMMAF-HAR comprises three interconnected modules: the Dynamic Visual Chronometer Module (DVCM) for capturing physical time scales from video, the Modality-Specific Enhancement and Feature Extractor (MSEFE) for tailored processing of non-visual data (e.g., IMU, acoustic), and the Context-Adaptive Fusion and Classifier (CAFC) for intelligent, dynamic fusion based on environmental context and data quality. Extensive experiments on the challenging MobiAct++ dataset demonstrated DMMAF-HAR's superior performance (89.3% accuracy, 88.9% F1-Score), significantly surpassing existing single-modal and multi-modal HAR approaches. Our system also exhibited exceptional robustness in adverse conditions (low light, occlusion, noise) and proved computationally efficient for real-time applications. DMMAF-HAR's dynamic adaptability and high accuracy pave the way for more reliable and intuitive intelligent systems in smart homes, health monitoring, and advanced robotics. Future work includes investigating more sophisticated context estimation techniques and extending the framework to wider sensor modalities.

References

1. Gu, J.; Stefani, E.; Wu, Q.; Thomason, J.; Wang, X. Vision-and-Language Navigation: A Survey of Tasks, Methods, and Future Directions. In Proceedings of the Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, 2022, pp. 7606–7623. https://doi.org/10.18653/v1/2022.acl-long.524.
2. Hou, S.; Lin, F.; Huang, Y.; Peng, Z.; Xiao, B. Mobile Augmented Reality Framework with Fusional Localization and Pose Estimation. *CoRR* **2025**, *abs/2501.03336*, [2501.03336]. https://doi.org/10.48550/ARXIV.2501.03336.
3. Fetahu, B.; Chen, Z.; Kar, S.; Rokhlenko, O.; Malmasi, S. MultiCoNER v2: a Large Multilingual dataset for Fine-grained and Noisy Named Entity Recognition. In Proceedings of the Findings of the Association for Computational Linguistics: EMNLP 2023. Association for Computational Linguistics, 2023, pp. 2027–2051. https://doi.org/10.18653/v1/2023.findings-emnlp.134.
4. Ju, X.; Zhang, D.; Xiao, R.; Li, J.; Li, S.; Zhang, M.; Zhou, G. Joint Multi-modal Aspect-Sentiment Analysis with Auxiliary Cross-modal Relation Detection. In Proceedings of the Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 2021, pp. 4395–4405. https://doi.org/10.18653/v1/2021.emnlp-main.360.
5. Xu, X.; Wang, Y.; Xu, D.; Peng, Y.; Zhang, C.; Jia, J.; Chen, B. Vsegan: Visual speech enhancement generative adversarial network. In Proceedings of the ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 7308–7311.

 doi:10.20944/preprints202603.2222.v1

6. Lin, F.; Gao, S.; Tang, Y.; Ma, X.; Murakami, R.; Zhang, Z.; Obayemi, J.; Soboyejo, W.W.O.; Zhang, H.K. SPADE: Spectroscopic Photoacoustic Denoising using an Analytical and Data-free Enhancement Framework. *CoRR* **2024**, *abs/2412.12068*, [2412.12068]. https://doi.org/10.48550/ARXIV.2412.12068.
7. Xu, C.; Chen, Y.Y.; Nayyeri, M.; Lehmann, J. Temporal Knowledge Graph Completion using a Linear Temporal Regularizer and Multivector Embeddings. In Proceedings of the Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2021, pp. 2569–2578. https://doi.org/10.18653/v1/2021.naacl-main.202.
8. Gao, X.; Wu, M.; Yang, S.; Yu, J.; Taghavi, P.; Lin, F.; Tu, Z. The Pulse of Motion: Measuring Physical Frame Rate from Visual Dynamics. *arXiv preprint arXiv:2603.14375* **2026**.
9. Zhao, Y.; Cai, X.; Wu, Y.; Zhang, H.; Zhang, Y.; Zhao, G.; Jiang, N. MoSE: Modality Split and Ensemble for Multimodal Knowledge Graph Completion. In Proceedings of the Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 2022, pp. 10527–10536. https://doi.org/10.18653/v1/2022.emnlp-main.719.
10. Li, Z.; Xu, B.; Zhu, C.; Zhao, T. CLMLF:A Contrastive Learning and Multi-Layer Fusion Method for Multimodal Sentiment Detection. In Proceedings of the Findings of the Association for Computational Linguistics: NAACL 2022. Association for Computational Linguistics, 2022, pp. 2282–2294. https://doi.org/10.18653/v1/2022.findings-naacl.175.
11. Li, Z.; Jin, X.; Guan, S.; Li, W.; Guo, J.; Wang, Y.; Cheng, X. Search from History and Reason for Future: Two-stage Reasoning on Temporal Knowledge Graphs. In Proceedings of the Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, 2021, pp. 4732–4743. https://doi.org/10.18653/v1/2021.acl-long.365.
12. Xu, X.; Tu, W.; Yang, Y. CASE-Net: Integrating local and non-local attention operations for speech enhancement. *Speech Communication* **2023**, *148*, 31–39.
13. Xu, X.; Tu, W.; Yang, Y. Pcnn: A lightweight parallel conformer neural network for efficient monaural speech enhancement. *arXiv preprint arXiv:2307.15251* **2023**.
14. Zhang, H.; Wang, Y.; Yin, G.; Liu, K.; Liu, Y.; Yu, T. Learning Language-guided Adaptive Hyper-modality Representation for Multimodal Sentiment Analysis. In Proceedings of the Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics, 2023, pp. 756–767. https://doi.org/10.18653/v1/2023.emnlp-main.49.
15. Tang, J.; Li, K.; Jin, X.; Cichocki, A.; Zhao, Q.; Kong, W. CTFN: Hierarchical Learning for Multimodal Sentiment Analysis Using Coupled-Translation Fusion Network. In Proceedings of the Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, 2021, pp. 5301–5311. https://doi.org/10.18653/v1/2021.acl-long.412.
16. Zhang, D.; Li, S.; Zhang, X.; Zhan, J.; Wang, P.; Zhou, Y.; Qiu, X. SpeechGPT: Empowering Large Language Models with Intrinsic Cross-Modal Conversational Abilities. In Proceedings of the Findings of the Association for Computational Linguistics: EMNLP 2023. Association for Computational Linguistics, 2023, pp. 15757–15773. https://doi.org/10.18653/v1/2023.findings-emnlp.1055.
17. Wu, Y.; Zhan, P.; Zhang, Y.; Wang, L.; Xu, Z. Multimodal Fusion with Co-Attention Networks for Fake News Detection. In Proceedings of the Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021. Association for Computational Linguistics, 2021, pp. 2560–2569. https://doi.org/10.18653/v1/2021.findings-acl.226.
18. Yang, J.; Wang, Y.; Yi, R.; Zhu, Y.; Rehman, A.; Zadeh, A.; Poria, S.; Morency, L.P. MTAG: Modal-Temporal Attention Graph for Unaligned Human Multimodal Language Sequences. In Proceedings of the Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2021, pp. 1009–1021. https://doi.org/10.18653/v1/2021.naacl-main.79.
19. Wang, X.; Gui, M.; Jiang, Y.; Jia, Z.; Bach, N.; Wang, T.; Huang, Z.; Tu, K. ITA: Image-Text Alignments for Multi-Modal Named Entity Recognition. In Proceedings of the Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2022, pp. 3176–3189. https://doi.org/10.18653/v1/2022.naacl-main.232.

 doi:10.20944/preprints202603.2222.v1

20. Li, Z.; Tang, F.; Zhao, M.; Zhu, Y. EmoCaps: Emotion Capsule based Model for Conversational Emotion Recognition. In Proceedings of the Findings of the Association for Computational Linguistics: ACL 2022. Association for Computational Linguistics, 2022, pp. 1610–1618. https://doi.org/10.18653/v1/2022.findings-acl.126.
21. Zhao, J.; Li, R.; Jin, Q. Missing Modality Imagination Network for Emotion Recognition with Uncertain Missing Modalities. In Proceedings of the Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, 2021, pp. 2608–2618. https://doi.org/10.18653/v1/2021.acl-long.203.
22. Dai, W.; Cahyawijaya, S.; Liu, Z.; Fung, P. Multimodal End-to-End Sparse Model for Emotion Recognition. In Proceedings of the Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2021, pp. 5305–5316. https://doi.org/10.18653/v1/2021.naacl-main.417.
23. Xu, L.; Chia, Y.K.; Bing, L. Learning Span-Level Interactions for Aspect Sentiment Triplet Extraction. In Proceedings of the Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, 2021, pp. 4755–4766. https://doi.org/10.18653/v1/2021.acl-long.367.
24. Zhang, K.; Zhang, K.; Zhang, M.; Zhao, H.; Liu, Q.; Wu, W.; Chen, E. Incorporating Dynamic Semantics into Pre-Trained Language Model for Aspect-based Sentiment Analysis. In Proceedings of the Findings of the Association for Computational Linguistics: ACL 2022. Association for Computational Linguistics, 2022, pp. 3599–3610. https://doi.org/10.18653/v1/2022.findings-acl.285.
25. Li, J.; Xu, K.; Li, F.; Fei, H.; Ren, Y.; Ji, D. MRN: A Locally and Globally Mention-Based Reasoning Network for Document-Level Relation Extraction. In Proceedings of the Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021. Association for Computational Linguistics, 2021, pp. 1359–1370. https://doi.org/10.18653/v1/2021.findings-acl.117.
26. Chen, T.; Shi, H.; Tang, S.; Chen, Z.; Wu, F.; Zhuang, Y. CIL: Contrastive Instance Learning Framework for Distantly Supervised Relation Extraction. In Proceedings of the Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, 2021, pp. 6191–6200. https://doi.org/10.18653/v1/2021.acl-long.483.
27. Xu, H.; Ghosh, G.; Huang, P.Y.; Arora, P.; Aminzadeh, M.; Feichtenhofer, C.; Metze, F.; Zettlemoyer, L. VLM: Task-agnostic Video-Language Model Pre-training for Video Understanding. In Proceedings of the Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021. Association for Computational Linguistics, 2021, pp. 4227–4239. https://doi.org/10.18653/v1/2021.findings-acl.370.
28. Hollenstein, N.; Pirovano, F.; Zhang, C.; Jäger, L.; Beinborn, L. Multilingual Language Models Predict Human Reading Behavior. In Proceedings of the Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Association for Computational Linguistics, 2021, pp. 106–123. https://doi.org/10.18653/v1/2021.naacl-main.10.