

Enhance-then-Balance Modality Collaboration for Robust Multimodal Sentiment Analysis

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Abstract

Multimodal sentiment analysis (MSA) integrates heterogeneous text, audio, and visual signals to infer human emotions. While recent approaches leverage cross-modal complementarity, they often struggle to fully utilize weaker modalities. In practice, dominant modalities tend to overshadow non-verbal ones, inducing modality competition and limiting overall contributions. This imbalance degrades fusion performance and robustness under noisy or missing modalities. To address this, we propose a novel model, *Enhance-then-Balance Modality Collaboration framework (EBMC)*. EBMC improves representation quality via semantic disentanglement and cross-modal enhancement, strengthening weaker modalities. To prevent dominant modalities from overwhelming others, an *Energy-guided Modality Coordination mechanism* achieves implicit gradient rebalancing via a differentiable equilibrium objective. Furthermore, *Instance-aware Modality Trust Distillation* estimates sample-level reliability to adaptively modulate fusion weights, ensuring robustness. Extensive experiments demonstrate that EBMC achieves state-of-the-art or competitive results and maintains strong performance under missing-modality settings. Our codes are available at <https://github.com/kangverse/EBMC>.

1. Introduction

Multimodal sentiment analysis (MSA) aims to capture the complex patterns of human emotional expression by integrating information from text, audio, and visual signals [14, 36, 59, 61]. Compared with unimodal approaches [47], multimodal learning can exploit complementary cues across modalities, enabling more nuanced and robust emotion understanding in real-world scenarios [15, 19]. With the widespread availability of multimodal

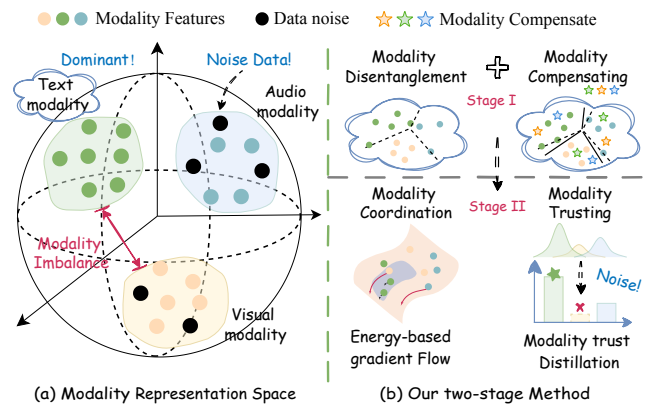


Figure 1. Illustration of modality imbalance: text tends to dominate learning while weaker modalities are easily suppressed and affected by noisy samples. Our two-stage framework first performs modality disentanglement and compensation (Stage I), then applies an energy-based gradient flow for modality coordination and sample-aware reliability for trusting (Stage II), leading to balanced multimodal optimization and ensure robustness.

data [1, 17, 63], MSA has shown promise in applications such as intelligent human-computer interaction [8, 68] and mental health monitoring [64]. However, due to the inherent heterogeneity across modalities and their unequal reliability [11, 33, 53], achieving robust sentiment analysis at a near-human cognitive level remains challenging.

Existing research has made substantial progress in multimodal representation learning and fusion. Early [36, 59], late [15, 57, 70], and hybrid fusion strategies [25, 31, 67] attempt to aggregate information at different stages of the pipeline. Meanwhile, modality semantic disentanglement methods [24, 48] isolate shared and modality-specific components, allowing models to better characterize the contribution of each modality to emotion expression. These advances improve feature expressiveness and cross-modal interaction to some extent. Nevertheless, most existing methods implicitly assume that *all modalities contribute in a*

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balanced and reliable manner, and therefore offer **limited treatment of modality imbalance and robustness**.

Recent multimodal learning systems face a persistent challenge: *the expressive power and gradient contributions of different modalities are inherently imbalanced*. Prior work [9, 11, 49] shows that text consistently dominates prediction, while audio and visual signals remain under-exploited due to weaker or noisier emotional cues. As illustrated in Fig. 1(a), weaker modalities are more vulnerable to **noise data**, sparse cues, and missing signals, making them difficult to optimize and easily overshadowed during training. This imbalance further induces *modality competition* [10, 11, 16, 33]: dominant modalities accumulate larger gradients and reinforce their own representations, while weaker modalities receive insufficient updates. Over time, this creates a “Matthew effect” where weak modalities become increasingly marginalized, *especially under noisy or real-world conditions*.

To address these challenges, we propose a robust Enhance-then-Balance Modality Collaboration framework (EBMC) with a two-stage design in Fig. 1(b). **Stage I** enhances unimodal representations: Modality Semantic Disentanglement (MSD) disentangles shared/specific semantics, and Cross-modal Complementary Enhancement (CCE) reinforces weak modalities through cross-modal complementary cues. **Stage II** then balances modality contributions: Energy-guided Modality Coordination (EMC) module introduces an energy-based coordination mechanism that aligns modality optimization dynamics, and Instance-aware Modality Trust Distillation (IMTD) module further estimates modality reliability from probabilistic teacher signals to adaptively adjust fusion weights.

We conduct extensive experiments on three widely used benchmarks: CMU-MOSI, CMU-MOSEI, and IEMOCAP. EBMC achieves superior or highly competitive performance across all datasets. Given the close relationship between MSA and emotion recognition in conversations (ERC) [20, 44], we further transfer EBMC to ERC and observe consistent gains, demonstrating its generalizability. In addition, experiments under modality-missing and intra-modality missingness scenarios (Sec. 4.4) show that EBMC suffers substantially smaller performance degradation than existing baselines, confirming its robustness in more realistic, imperfect multimodal environments. The main contributions are summarized as follows:

- We introduce a weak-modality enhancement mechanism that disentangles shared/specific semantics and performs cross-modal compensation to strengthen weak modalities and improve emotion discrimination.
- To mitigate modality competition, we present the first EBM-inspired modality coordination mechanism that rebalances modalities via energy potentials and gradient-flow dynamics.

- We design an instance-aware modality trust distillation (IMTD) module that estimates sample-level modality reliability and adaptively modulates fusion weights, improving robustness under noisy or missing modalities.
- Extensive experiments on MOSI, MOSEI, and IEMOCAP demonstrate superior or comparable performance. We further validate EBMC on ERC tasks and under modality-missing scenarios, confirming its effectiveness.

2. Related works

Multimodal Sentiment Analysis. Multimodal Sentiment Analysis (MSA) integrates textual, acoustic, and visual cues to capture richer affective information. Existing approaches primarily fall into two directions: representation learning and multimodal fusion. Representation learning methods focus on disentangling shared and modality-specific semantics, such as MISA [15], as well as extensions using multimodal distillation [24] and contrastive learning [57]. Fusion approaches explore more adaptive strategies, including attention-based [37, 39], graph-based [3, 56], gating-based [67], and hierarchical models [56]. Recent work [25, 31] further enhance modality alignment prior to fusion. Although effective, these methods often overlook modality imbalance and struggle under noisy or missing modalities.

Imbalanced Multimodal Learning. Modality imbalance occurs when dominant modalities overshadow weaker ones during joint training [5, 16, 55]. To alleviate this, prior works dynamically adjust learning rates or gradients across modalities based on loss signals or learning dynamics [33, 49, 53]. Other approaches redesign the objective to curb dominant modalities or boost weaker ones, including Fisher-information regularization [18], decoupled fusion streams [5], detached unimodal encoders with contrastive objectives [10], and prototype-based rebalancing [9]. While effective at the optimization level, these methods offer limited semantic enhancement for weaker modalities.

Robust Multimodal Learning. Robust learning targets performance stability against modality noise, degradation, and missingness. Uncertainty modeling methods, including hyperdimensional uncertainty quantification [4] and aleatoric-guided fusion [13], improve confidence calibration and noise robustness, while prototype-based updating strategies further mitigate intra-modal variation [23]. To handle missing modalities, recent works adopt self-distillation or cross-modal reconstruction [21, 38], shared-specific representation learning [19], or prompting-based alignment [52]. Robustness is also enhanced through multi-scale attention fusion [29, 41] and text-centric adversarial prompting [42]. In contrast, EBMC embeds robustness directly into the core learning process by adaptively suppressing noisy modalities and enhancing cross-modal complementarity for stable and reliable performance.

3. Methodology

3.1. Preliminaries

In MSA task, the input comprises a set of modalities $M = \{l, v, a\}$ corresponding to text, visual, and audio signals. Each modality is encoded as a feature sequence $X_m \in \mathbb{R}^{T_m \times d_m}$, where T_m is the sequence length and d_m the feature dimension. Given multimodal inputs $X_{m \in M}$, the objective is to predict the sentiment category or intensity. As illustrated in Fig. 2, our framework EBMC adopts a two-stage design: MSD (Sec. 3.2) and CCE (Sec. 3.3) first enhance weak modality representations while preserving unimodal predictive capability, and EMC (Sec. 3.4) together with IMTD (Sec. 3.5) then mitigates modality competition and strengthens robustness.

3.2. Modality Semantic Disentangle

Directly fusing raw modality features often introduces semantic interference and allows dominant modalities to overshadow weaker ones, limiting the contribution of non-dominant modalities [9, 10, 53]. To enable effective multimodal fusion while preserving unimodal predictive capability, we first perform semantic disentanglement for each modality. Specifically, the representation of each modality z_m is decomposed into a shared component z_m^c and a modality-specific component z_m^s :

$$z_m^c = D_m^c(z_m), \quad z_m^s = D_m^s(z_m), \quad (1)$$

where D_m^c and D_m^s are lightweight MLP sub-networks that extract cross-modal shared semantics and modality-specific information (e.g., prosody or facial expression details). To ensure clear functional separation between shared and specific components, multiple constraints are introduced. First, invariant alignment ensures that shared components across modalities are close in the semantic space, formulated via an InfoNCE [32] contrastive loss:

$$\mathcal{L}_{\text{inv}} = - \sum_i \log \frac{\exp(\sin(z_i^c, z_{\text{agg}}^c)/\tau)}{\sum_k \exp(\sin(z_i^c, z_k^c)/\tau)}. \quad (2)$$

Second, to avoid redundancy among modality-specific components, we minimize batch-wise cosine similarity, enforcing specific disentanglement:

$$\mathcal{L}_{\text{dis}} = \sum_{i \neq j} \sin(z_i^s, z_j^s). \quad (3)$$

In addition, to ensure each modality-specific component retains predictive capability, we employ a unimodal predictor T_m and define the unimodal task loss as:

$$\mathcal{L}_{\text{uni}} = \frac{1}{|M|} \sum_{m \in M} \ell(T_m(z_m^s), y), \quad (4)$$

where $\ell(\cdot, \cdot)$ is the task loss (e.g., cross-entropy or regression loss). The overall loss for MSD is:

$$\mathcal{L}_{\text{MSD}} = \mathcal{L}_{\text{inv}} + \lambda_1 \mathcal{L}_{\text{dis}} + \lambda_2 \mathcal{L}_{\text{uni}}, \quad (5)$$

where λ_1 and λ_2 are trade-off hyperparameters. By disentangling modality representations in this way, MSD suppresses semantic interference and provides clean, controllable features for subsequent cross-modal collaboration.

3.3. Cross-modal Complementary Enhancement

Although MSD preserves modality-specific information, the text modality still tends to dominate semantic discrimination, while visual and audio modalities often encode subtler emotional cues. To better leverage these weaker modalities, we introduce the Cross-modal Complementary Enhancement (CCE) module, which enriches each modality by incorporating complementary shared and specific components from other modalities.

Concretely, for modality m , CCE takes its own components (z_m^c, z_m^s) together with the shared and specific components from the remaining modalities (z_{-m}^c, z_{-m}^s), and feeds them into a lightweight enhancement network G_m to generate enhanced features:

$$\tilde{z}_m = G_m(z_m^c, z_{-m}^c, z_m^s, z_{-m}^s, \epsilon), \quad (6)$$

where ϵ is an optional stochastic perturbation that increases feature diversity. The training objective is designed to enforce semantic consistency and maintain downstream predictive correctness:

$$\mathcal{L}_{\text{CCE}} = \mathbb{E} \|\tilde{z}_m - z_m\|_2^2 + \gamma \ell(f(\tilde{z}_m, z_{-m}), y). \quad (7)$$

where $f(\cdot)$ denotes the downstream prediction head and γ balances the two terms. The reconstruction term preserves the original semantic structure of z_m , while the task loss ensures that the enhanced feature remains discriminative for the target task. In this way, CCE effectively amplifies the contribution of weaker modalities and provides more informative representations for subsequent EMC module.

3.4. Energy-guided Modality Coordination

To further address modality competition, we reinterpret multimodal coordination through the lens of Energy-based Models (EBMs). Rather than explicitly reweighting losses or manually correcting gradients, EMC constructs a structured multimodal energy landscape and performs coordination through both energy-gap minimization and energy-gradient dynamics. This provides a fully differentiable mechanism for suppressing dominant modalities and amplifying weaker ones during joint optimization.

Energy Function. For each modality m , we define a modality-specific energy potential that integrates semantic activation, task difficulty, and predictive reliability:

$$E(m) = \alpha \|z_m\|_2^2 + \beta \ell_m + \gamma u_m, \quad (8)$$

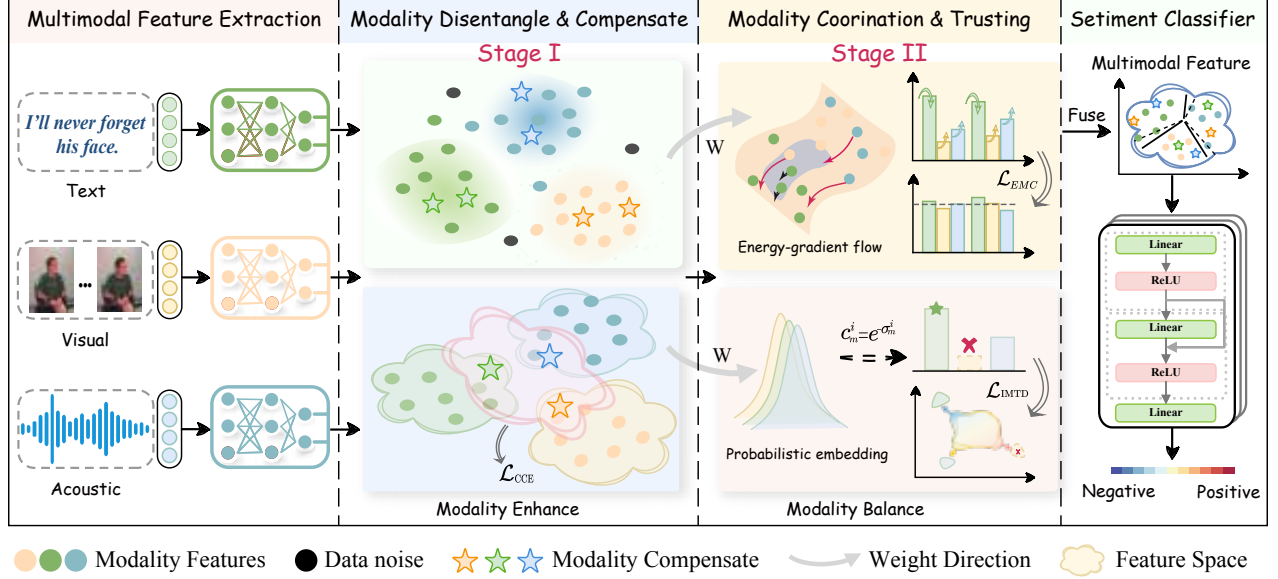


Figure 2. The overall architecture of our proposed model EBMC.

$$u_m = \mathbb{E}_i [H(p_{T_m}^i(y))] , H(p) = - \sum_y p(y) \log p(y). \quad (9)$$

where $\|z_m\|_2^2$ captures representation magnitude, ℓ_m is the modality-specific task loss, and u_m denotes predictive uncertainty. This formulation yields a multi-factor energy landscape in which weaker modalities typically exhibit higher energy due to noisier signals or less discriminative features. Refer to Appendix B for details.

Energy-gap Minimization. Dominant modalities often acquire disproportionately low energy, enabling them to overwhelm weaker ones. To prevent this imbalance, EMC enforces a global energy-equilibrium objective:

$$\mathcal{L}_{gap} = \sum_{i,j} (E(m_i) - E(m_j))^2. \quad (10)$$

Minimizing Eq. (10) encourages all modalities to converge toward a balanced regime, ensuring that under-utilized modalities receive increased optimization focus.

Energy-gradient Flow. Beyond matching energy magnitudes, EMC further regulates optimization dynamics by explicitly adopting an energy-descent update:

$$\Delta z_m = -\lambda \frac{\partial E(m)}{\partial z_m}. \quad (11)$$

This implicitly forms a negative-feedback mechanism: modalities with excessively low energy (over-confident or overly dominant) receive suppressive gradients, whereas high-energy modalities naturally obtain larger corrective gradients. Such dynamics approximate gradient flows in EBMs and provide an adaptive, self-correcting training trajectory. Combining the above components, the complete

EMC objective becomes:

$$\mathcal{L}_{EMC} = \mathcal{L}_{gap} + \delta \sum_m \left\| \frac{\partial E(m)}{\partial z_m} \right\|^2, \quad (12)$$

where the second term penalizes unstable or overly sharp energy gradients, promoting smoother energy flows and stable multimodal convergence.

3.5. Instance-aware Modality Trust Distillation

MSD and CCE alleviate modality imbalance at the representation level; however, traditional fusion schemes remain vulnerable to noise and missing modalities at the instance level [22, 26, 66]. To further enhance robustness, we introduce Instance-aware Modality Trust Distillation (IMTD), which uses probabilistic embeddings to estimate sample-specific modality confidence and adaptively weight modality contributions during distillation.

Specifically, for modality m , the teacher model T_m from MSD (Sec. 3.2) produces a predictive probability distribution $p_{T_m}(y)$ for each sample. We denote its mean and variance as μ_m^i and σ_m^i , where σ_m^i represents the predictive uncertainty of modality m for sample i . We convert the variance into a confidence score:

$$c_m^i = \exp(-\sigma_m^i), \quad (13)$$

so lower variance implies higher certainty and thus higher confidence. To avoid instability from excessively large variances, we introduce a soft normalization factor:

$$\rho_m^i = \frac{1}{\log(1 + \|\sigma_m^{2i}\|_1)}, \quad (14)$$

which suppresses the influence of unstable modalities and smooths the confidence distribution. The final adaptive distillation weight combines teacher confidence and normalized reliability:

$$\alpha_m^i = \frac{c_m^i \rho_m^i}{\sum_m c_m^i \rho_m^i}. \quad (15)$$

During distillation, the student’s fused prediction is aligned with the teacher outputs via a confidence-weighted KL divergence:

$$\mathcal{L}_{\text{IMTD}} = \sum_{m,i} \alpha_m^i \text{KL} \left(\sigma(z_{\text{fusion}}^i / \tau) \parallel \sigma(z_{T_m}^i / \tau) \right), \quad (16)$$

where $\sigma(\cdot)$ denotes the softmax function and τ is a temperature coefficient. IMTD assigns higher weights to reliable modalities and down-weights noisy ones at the sample level, providing a stable way to handle modality missingness and noise while enhancing robustness; further analyses will be discussed in Sec. 4.4.

3.6. Overall Training Objective

With the losses defined in Eq. (5) – Eq. (16), the overall EBMC training objective is:

$$\mathcal{L} = \mathcal{L}_{\text{task}} + \zeta \mathcal{L}_{\text{MSD}} + \beta \mathcal{L}_{\text{CCE}} + \gamma \mathcal{L}_{\text{EMC}} + \eta \mathcal{L}_{\text{IMTD}}. \quad (17)$$

$$\mathcal{L}_{\text{task}} = \frac{1}{N} \sum_{i=1}^N -y_i \log(\hat{y}_i) \quad (18)$$

This objective jointly drives disentanglement, complementary enhancement, balanced coordination, and reliability-aware fusion, with $\zeta, \beta, \gamma, \eta$ weighting each component.

4. Experiments

Datasets. To evaluate the generalizability of our framework for both MSA and ERC tasks, we conduct experiments on three widely used benchmark datasets: CMU-MOSI [63], CMU-MOSEI [1], and IEMOCAP [2]. CMU-MOSI contains 2,199 opinion video clips annotated with binary sentiment labels. CMU-MOSEI is a larger and more diverse dataset with 22,856 YouTube video segments. Both datasets are labeled with sentiment intensity scores from -3 (strongly negative) to $+3$ (strongly positive), enabling fine-grained regression-based evaluation. IEMOCAP, a standard benchmark for emotion recognition, consists of 4,453 video clips annotated with categorical emotions across approximately 12 hours of audiovisual recordings.

Evaluation Metrics. We report the average results over five runs with different random seeds. For MOSI and MOSEI, we evaluate EBMC performance using metrics including 2-class Accuracy (Acc-2), 7-class Accuracy (Acc-7), F1

score (F1), Correlation (Corr), and Mean Absolute Error (MAE). Following prior work conventions [61, 70], Acc-2 and F1 are reported in two forms (denoted as ‘-/-’): one with zero as negative/non-negative, and the other excluding zero as negative/positive. For IEMOCAP, as recommended by [22, 50], we evaluate the F1 score for four emotion categories (*happy, sad, angry, and neutral*).

Implementation Details. To ensure fair comparisons with previous studies, we use the same feature extraction settings. For language modality, we use BERT_{base} model [7] to obtain a 768-dimensional hidden state as the word features, and additionally incorporate 300-dimensional GloVe features [34] for consistency with prior ERC work on IEMOCAP. For the visual modality, we extract 35 facial action unit features using Facet, and for the acoustic modality, we use COVAREP [6] to obtain 74-dimensional low-level acoustic descriptors. Hyperparameters $\lambda_1, \lambda_2, \beta, \gamma, \eta$ are all set to 0.1, and ζ is set to 0.5 based on validation performance. All experiments are conducted on a RTX 4090 GPU (48GB) with a batch size of 64. Each stage of EBMC is trained for 100 epochs. Additional implementation details are provided in Appendix A.2.

4.1. Comparison with State-of-the-art Methods

We conduct a comprehensive comparison between our proposed EBMC and several representative SOTA models, including MuLT [43], SelfMM[60], ConKI [61], ConFEDE [57], CLGSI [58], MFON [69], EUAR [12], GLoMo [70], DEVA [54], Semi-IIN [27]. In addition, to evaluate the robustness of EBMC, we perform extensive experiments under modality-missing scenarios [21, 22, 26]. Further details can be found in Appendix A.1.

Results on the MSA dataset. Tab. 1 demonstrates that EBMC consistently outperforms existing SOTA methods across most evaluation metrics on the CMU-MOSI and CMU-MOSEI datasets. Notably, EBMC demonstrates marked improvements in Acc-7, outperforming Semi-IIN [27] by 1.89% on CMU-MOSI (50.34% vs. 46.50%) and by 1.1% on CMU-MOSEI (57.32% vs. 55.89%). This indicates that the complementary enhancement of weaker modalities allows the model to *better capture discriminative information* in samples with subtle emotional expressions. Furthermore, improvements are observed across other metrics; compared with GLoMo [70], EBMC achieves a 1.19% higher F1 score on CMU-MOSI (87.79% vs. 86.60%) and a 1.67% higher F1 score on CMU-MOSEI (88.07% vs. 86.40%). Overall, EBMC effectively disentangles shared and modality-specific information and enhances weaker modalities through the CCE module. In addition, we also employ the energy-based modality coordination mechanism to dynamically balance contributions across modalities, leading to consistently improved performance.

Table 1. Comparison with SOTA methods on the CMU-MOSI and CMU-MOSEI datasets. Bold indicates the best result, and underlining denotes the second-best. Note: ♡ and ◇ represents results obtained from [70] and [61], respectively. * indicates reproduced results from the public code. Other results taken directly from the original paper. See details in Sec. 4.1.

Method	CMU-MOSI					CMU-MOSEI				
	Acc-2(↑)	F1(↑)	Acc-7(↑)	Corr(↑)	MAE(↓)	Acc-2(↑)	F1(↑)	Acc-7(↑)	Corr(↑)	MAE(↓)
MuLT♡ [43]	79.51/80.47	79.46/80.49	36.74	0.667	0.892	81.10/83.63	81.05/83.46	52.34	0.605	0.671
SelfMM◇ [60]	82.54/84.77	84.42/85.95	45.79	0.795	0.712	82.68/84.96	82.95/84.93	53.46	0.767	0.529
ConKI◇ [61]	84.37/86.13	84.33/86.13	48.43	0.816	<u>0.681</u>	82.73/86.25	83.08/86.15	54.25	0.782	0.529
ConFEDE [57]	84.17/85.52	84.13/85.52	42.27	0.742	0.784	81.65/85.82	82.17/85.83	54.86	0.780	0.522
CLGSI [58]	83.97/86.43	83.63/86.25	47.96	0.790	0.703	84.01/86.32	84.21/86.18	54.56	0.763	0.532
MFON [69]	84.84/86.89	84.75/86.86	44.90	0.797	0.725	82.70/86.32	83.13/86.29	53.72	0.780	0.528
EUAR* [12]	83.24/84.58	84.22/84.58	48.18	0.789	0.711	82.20/85.64	82.02/85.46	51.07	0.785	0.596
GLoMo♡ [70]	84.10/86.70	83.90/86.60	48.30	0.782	0.718	83.70/86.50	84.00/86.40	55.00	0.771	0.539
DEVA [54]	84.40/86.29	84.48/86.30	46.32	0.787	0.730	83.26/86.13	82.93/86.21	52.26	0.769	0.541
Semi-IIN [27]	85.28/87.04	85.19/87.00	46.50	<u>0.822</u>	0.679	84.98/87.70	85.27/87.65	<u>55.89</u>	<u>0.804</u>	0.497
EBMC(ours)	86.26/87.84	86.20/87.79	50.34	0.833	0.694	86.04/88.10	86.23/88.07	57.32	0.824	0.505

Table 2. Comparison of F1-scores across different methods on the IEMOCAP dataset. Please see Sec. 4.1 for details.

Methods	Happy	Sad	Angry	Neutral	Avg.
Self-MM [60]	90.8	86.7	88.4	72.7	84.65
MCTN [35]	83.1	82.8	84.6	67.7	79.55
TransM [51]	85.5	84.0	86.1	67.1	80.68
SMIL [28]	86.8	85.2	84.9	68.9	81.45
GCNet [26]	87.7	86.9	85.2	71.1	82.73
UMDF [21]	87.9	86.5	85.8	70.5	82.68
CorrKD [22]	87.5	85.9	86.1	71.5	82.75
DMD [24]	91.1	88.4	88.6	72.2	85.08
EBMC	92.0	89.5	90.3	73.6	86.35

Results on the ERC dataset. To further evaluate the generalization ability of EBMC, we assess its performance on the ERC task. As shown in Tab. 2, EBMC demonstrates strong performance on the IEMOCAP dataset across all four emotion categories. The strongest baseline DMD [24], records an average F1-score of 85.08%, whereas EBMC achieves 86.35%, reflecting a 1.27% improvement. Notably, ERC involves finer-grained emotion categories, where human emotional expression can emphasize different cues, and certain signals may be more salient in audio or visual modalities. Moreover, Tab. 2 also shows that EBMC achieves particularly pronounced gains in *Happy* and *Angry* category, indicating enhanced discriminative capability in capturing emotional intensity and semantic details. Overall, EBMC can excel high-level performance on fine-grained, complex ERC scenarios, further validating the effectiveness of its complementary enhancement and energy-based modality coordination mechanisms.

4.2. Robust Analysis on Incomplete Conditions

To comprehensively evaluate the performance of EBMC under various incomplete modality conditions, we compared it with other methods [12, 26, 35] on the CMU-MOSEI dataset. As shown in Tab. 3, EBMC achieves the highest F1 scores under almost all missing modality conditions.

Table 3. Comparison of performance under six incomplete modality testing conditions on CMU-MOSEI datasets. Refer to Sec. 4.2.

Models	Testing Conditions						Avg.
	{A}	{T}	{V}	{A,V}	{A,T}	{T,V}	
Self-MM [60]	43.57	71.53	37.61	49.52	75.91	74.62	58.79
CubeMLP [40]	39.54	67.52	32.58	48.54	71.69	70.06	54.99
MCTN [35]	62.72	75.50	59.46	64.84	76.64	77.13	69.38
TransM [51]	63.68	77.98	58.67	62.24	80.46	78.61	70.27
GCNet [26]	66.54	80.52	61.83	69.21	81.96	81.15	73.54
DMD [22]	46.18	70.26	39.84	52.70	74.78	72.45	59.37
CorrKD [22]	66.09	80.76	62.30	71.92	81.74	81.28	74.02
EUAR [12]	60.70	85.20	65.30	65.30	85.10	86.00	74.50
EBMC(Ours)	71.67	84.79	70.05	73.34	86.76	86.90	78.92

We observe the following: (i) Competitor methods *perform significantly worse in single-modal conditions*, especially when only visual or audio modalities are available. EBMC effectively mitigates this issue. In the initial stage, MSD and CCE modules are able to learn useful information even with missing modalities. (ii) Modality missingness leads to a decline in performance across all modalities, which further highlights the *heterogeneity between modalities*. As the number of modalities increases, integrating complementary information from different modalities can effectively enhance the emotional semantics in the joint representation. These results demonstrate the superiority of EBMC in multi-modal missingness scenarios, enabling the model to fully leverage the potential of remaining modalities and compensate for the impact of missing information.

4.3. Ablation Studies

To assess the contribution of each key component in EBMC, we conduct ablation studies on the CMU-MOSI and CMU-MOSEI datasets. **Firstly**, as shown in Tab. 4, removing the MSD module significantly impairs the model’s ability to disentangle shared and modality-specific information, leading to a decrease in F1 by 1.63% on CMU-MOSI and 1.76% on CMU-MOSEI. **Similarly**, omitting the CCE module weakens the enhancement of weaker modalities, resulting

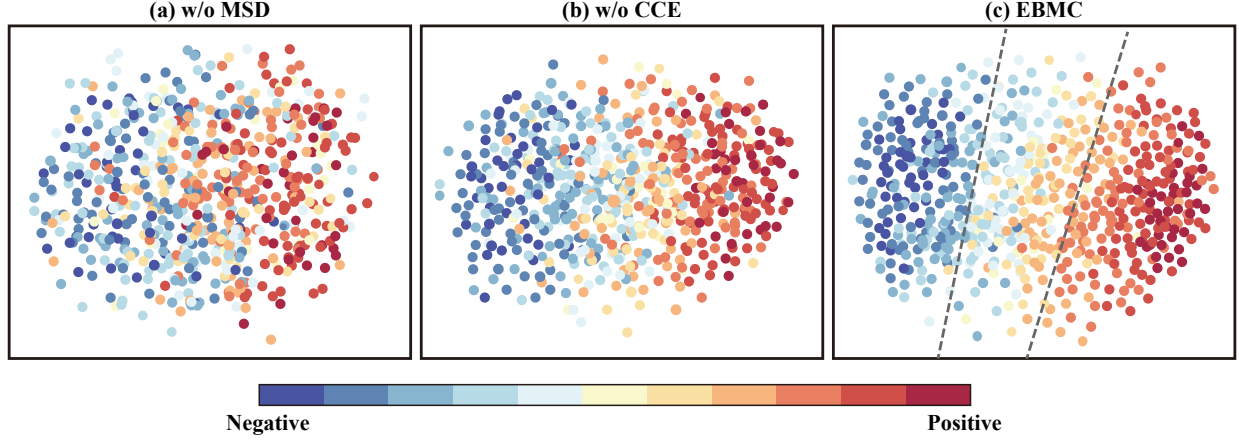


Figure 3. T-SNE visualization of features distribution on CMU-MOSI. The closer color is to red, the more positive sentiment. EBMC demonstrates superior performance in MSA. Please refer to Sec. 4.4.

Table 4. Ablation studies for each module in our proposed EBMC on CMU-MOSI and CMU-MOSEI datasets. Refer to Sec. 4.3.

Model	CMU-MOSI		CMU-MOSEI	
	Acc-2(↑)	F1(↑)	Acc-2(↑)	F1(↑)
EBMC	86.26/87.84	86.20/87.79	86.04/88.10	86.23/88.07
w/o MSD	84.37/86.23	84.30/86.16	84.24/86.32	84.16/86.31
w/o CCE	84.92/86.98	84.87/86.90	84.55/86.96	84.52/86.89
w/o EMC	83.54/85.41	83.56/85.32	83.51/85.12	83.47/85.20
w/o IMTD	85.35/87.01	85.24/86.77	85.26/87.15	84.96/87.09

in F1 reductions of 0.89% and 1.18%, respectively. The exclusion of the EMC module severely disrupts modality coordination, causing the largest F1 drop of 2.43% and 2.87%. **Finally**, removing the IMTD module, which ensures the adaptive weighting of modalities based on sample-level reliability, leads to a reduction of 1.02% and 0.98% in F1 on the two datasets. IMTD is crucial for modality missingness, as further discussed in Sec. 4.4 (Q3). These findings highlight the critical role of each component in EBMC, emphasizing their individual contributions to improving discriminative multimodal feature learning and overall robustness.

4.4. Analyses and Discussions

To better assess the effectiveness of EBMC, we conduct in-depth analyses to answer the following key questions:

Q1: How does weak modality enhancement improve emotion classification performance? To evaluate the effectiveness of MSD and CCE, we conduct ablation studies and use t-SNE [30] for 2D visualization of high-dimensional features. Fig. 3a (w/o MSD) shows a mixed feature distribution with unclear emotional boundaries, indicating that without semantic alignment, the model struggles to fuse information, resulting in scattered features and low emotional category distinction. Introducing MSD (Fig. 3b) improves feature distribution, making emo-

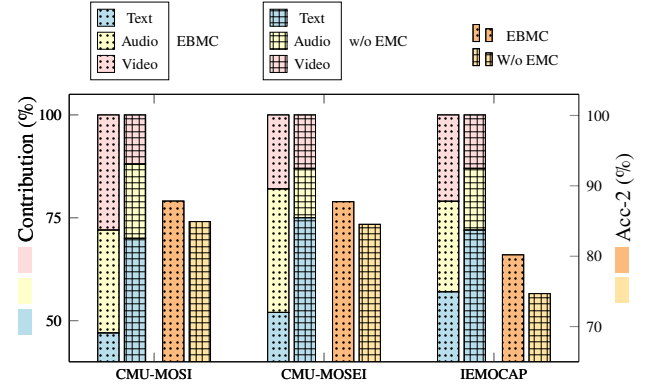


Figure 4. The impact of EMC on modality contributions and overall performance. The dual y-axes show the average contribution of each modality (left) and the corresponding Acc-2 score (right). Please refer to Sec. 4.4. Best viewed in color.

tional boundaries clearer, though scattered points remain in transition areas due to weak modality signals in ambiguous samples. MSD aligns shared semantic components but doesn't fully compensate for weak modality signals. With CCE (Fig. 3c), scattered points cluster into corresponding emotional categories, enhancing weak modality representation and improving emotion classification accuracy. These results demonstrate that weak modality enhancement addresses modality heterogeneity, enhances weak modality representation, and improves classification accuracy.

Q2: How does energy-driven modality collaboration alleviate the modality competition issue? EMC addresses modality competition by dynamically balancing the contributions of each modality during training. As shown in Fig. 4, without EMC, the textual modality dominates with over 50% contribution on all three datasets, suppressing audio and video signals and leading to imbalanced multimodal fusion. With EMC, the contribution distribution across modalities improves significantly: text dominance

Table 5. Robustness comparison of overall performance on the CMU-MOSI and CMU-MOSEI datasets under intra-modality missingness, simulated by randomly dropping frame-level features at varying rates ($p \in \{0, 0.1, \dots, 0.9\}$). Refer to Sec. 4.4 for details.

Methods	CMU-MOSI					CMU-MOSEI				
	Acc-2($\uparrow$)	F1($\uparrow$)	Acc-7($\uparrow$)	Corr($\uparrow$)	MAE($\downarrow$)	Acc-2($\uparrow$)	F1($\uparrow$)	Acc-7($\uparrow$)	Corr($\uparrow$)	MAE($\downarrow$)
MISA [15]	70.33/71.49	70.00/71.28	29.85	0.524	1.085	75.82/71.27	68.73/63.85	40.84	0.503	0.780
Self-MM [60]	69.26/70.51	67.54/66.60	29.55	0.512	1.070	77.42/73.89	72.31/68.92	44.70	0.498	0.695
MMIM [14]	67.06/69.14	64.04/66.65	31.30	0.507	1.077	75.89/73.32	70.32/68.72	40.75	0.489	0.739
CENET [45]	67.73/71.46	64.85/68.41	30.38	0.504	1.080	77.34/74.67	74.08/70.68	47.18	0.535	0.685
TETFN [46]	67.68/69.76	63.29/65.69	30.30	0.507	1.087	67.68/69.76	63.29/65.69	30.30	0.508	1.087
TFR-Net [62]	66.35/68.15	60.06/61.73	29.54	0.459	1.200	77.23/73.62	71.99/68.80	46.83	0.489	0.697
ALMT [65]	68.39/70.40	71.80/72.57	30.30	0.498	1.083	77.54/76.64	78.03/77.14	40.92	0.481	0.674
LNLN [66]	70.94/72.55	71.25/72.73	34.26	0.527	1.046	78.19/76.30	79.95/77.77	45.42	0.530	0.692
EBMC(Ours)	72.30/73.48	72.19/74.25	34.65	0.545	0.994	78.56/76.93	80.17/78.32	45.69	0.588	0.680

is reduced while audio and video contributions increase, resulting in a more balanced utilization of all modality information. This rebalancing directly translates to performance gains, as reflected by consistently higher Acc-2 scores across MOSI, MOSEI, and IEMOCAP. These results demonstrate that EMC effectively reduces modality competition, ensuring weaker modalities are not overshadowed, and yielding a more comprehensive representation that enhances performance in both MSA and ERC tasks.

Q3: What are the advantages of instance-aware modality trust distillation? We follow prior works [62, 66] by randomly dropping frame-level features at varying rates ($p \in \{0, 0.1, \dots, 0.9\}$) to simulate intra-modality missingness, and average results across all rates to measure robustness. As shown in Tab. 5, EBMC consistently outperforms all baselines on both datasets. On CMU-MOSI, it surpasses LNLN [66] by 1.52% in F1 and 0.39% in Acc-7, while reducing MAE from 1.046 to 0.994; similar gains hold on CMU-MOSEI, with Corr improving by 0.058. This robustness stems from the IMTD mechanism, which dynamically estimates per-sample modality reliability at inference time. When a modality is heavily corrupted, IMTD suppresses its contribution and up-weights more reliable modalities, enabling fine-grained rebalancing that fixed-weight or modality-level fusion strategies [62, 66] cannot achieve. As a result, EBMC retains discriminative cross-modal information under high noise and yields better-calibrated sentiment intensity predictions, as evidenced by consistent Corr gains.

4.5. Case Study

We compare EBMC with strong baselines on IEMOCAP samples. For clear emotional expressions (Fig. 5a), all models correctly recognize the sentiment. When emotional intensity is low—for example, neutral utterances with flat prosody or weakly negative expressions with minimal facial cues—baseline models tend to over-rely on textual polarity. As a result, they often mispredict the emotion, as shown in Fig. 5c where the true Neutral label is incorrectly

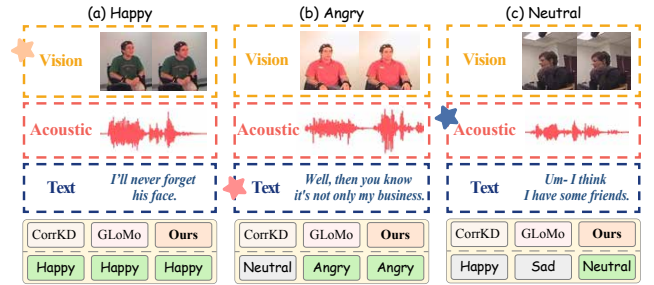


Figure 5. Comparison of EBMC and baseline predictions on the test sets of IEMOCAP. Refer to Sec. 4.5.

classified as Happy or Sad. In contrast, EBMC leverages enhanced audio-visual signals through CCE and mitigates textual dominance via EMC, enabling the model to capture weak prosody, subtle facial movements, and other non-verbal markers that better reflect the true emotional state. Overall, these cases demonstrate EBMC’s superiority in discerning subtle emotions, resolving cross-modal imbalance, and achieving robust multimodal inference.

5. Conclusion

In this work, we present a simple yet effective Enhance-then-Balance Modality Collaboration (EBMC) framework, suitable for both full-modality and modality-missing scenarios. EBMC adopts a two-stage design: the first stage extracts and aligns semantic information from each modality, preserving unimodal peak prediction capability; the second stage introduces adaptive fusion using EMC and IMTD to optimize the contributions of each modality. Extensive experiments demonstrate the superiority and robustness of EBMC. Ablation studies and further analyses confirm that enhancing weak modalities and dynamically adjusting modality contributions significantly improve model performance. Moreover, EBMC offers a unified perspective that bridges representation enhancement and modality coordination, yielding consistent gains across diverse emotion recognition tasks. Its modular design also makes EBMC readily applicable to broader multimodal learning settings.

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