Improved Multi-Modality Collaborative Learning for Multimodal Sentiment Analysis

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***Abstract*—Multimodal Sentiment Analysis (MSA) aims to identify emotional states by integrating visual, audio, and textual signals from user interactions. While recent methods like MMCL have explored contrastive and reinforcement-based strategies to manage modality heterogeneity, these approaches often suffer from complex training procedures and sensitivity to reward tuning. In this work, we propose a simplified yet effective framework that leverages attention-guided mechanisms to disentangle and align multimodal features without relying on reinforcement learning.**

Our model introduces a lightweight decoupling module that separates modality-common and modality-specific features through semantic correlation scoring. To extract enhanced and complementary representations, we apply cross-modal attention, allowing shared information to be refined while preserving emotion-specific cues. By removing policy-reward components and replacing them with interpretable transformer-based interactions, our approach improves both training stability and overall performance.

Experimental results on benchmark datasets, including IEMOCAP and CMU-MOSI, demonstrate that our method effectively learns collaborative features across modalities and outperforms previous baselines in emotion classification tasks.

***Index Terms*—Multimodal sentiment analysis, MMCL, modality heterogeneity, attention mechanism, transformer, cross-modal fusion, IEMOCAP, CMU-MOSI.**

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I. Introduction

Multimodal Sentiment Analysis (MSA) aims to infer individuals' emotional states from video clips by leveraging information from multiple modalities—text, audio, and visual signals. MSA is widely used in fields such as human-computer interaction, intelligent healthcare, virtual assistants, and driver monitoring systems. Individuals naturally express emotions using a combination of spoken words, vocal tone, and facial expressions, which together provide complementary cues for understanding sentiment.

While these modalities are synchronized by the same underlying sentiment, differences in format, noise levels, semantic density, and timing create what is referred to as modality heterogeneity. Successfully modeling interactions between these heterogeneous signals is essential for improving sentiment recognition performance.

Recent research has shown promise by separating modality features into modality-common (shared across modalities) and modality-specific (unique to each modality) representations. Traditional methods such as subspace learning, adversarial networks, and transfer learning aim to disentangle these representations, often followed by fusion. However, these methods can be overly complex, require extensive parameter tuning, and may include noise or task-irrelevant components, which reduce robustness and generalization.

To address these limitations, we propose a simplified and interpretable attention-based multimodal sentiment analysis framework. Instead of relying on complex reinforcement learning mechanisms like policy networks and reward critics (as used in MMCL), our method uses attention-guided feature decoupling and transformer-based fusion.

First, we introduce a parameter-free decoupling module that separates modality-common and modality-specific features based on semantic similarity scores across temporal elements. This enables effective feature separation without learning additional parameters or requiring pre-training. Next, we apply cross-modal attention mechanisms that allow each modality to attend to relevant features from the others, enhancing the shared representations and preserving complementary emotion-specific cues. This design avoids the instability and sensitivity of policy-reward systems and improves training robustness.

Finally, we combine the enhanced and complementary representations into a unified joint representation, which is used for sentiment classification. Our model is lightweight, modular, and end-to-end trainable, making it suitable for real-world applications.

Key Contributions

- We propose a simplified, attention-driven architecture for MSA that effectively captures both enhanced and complementary features across modalities, eliminating the need for reinforcement learning or critic models.
- We design a parameter-free decoupling module that uses semantic correlation scores to extract modality-common and modality-specific features without pretraining or auxiliary loss functions.
- We introduce a cross-modal attention fusion mechanism that strengthens relevant signals across modalities and preserves discriminative features for sentiment classification.

- Our model achieves state-of-the-art performance on benchmark datasets (IEMOCAP and CMU-MOSI) with improved stability, interpretability, and ease of deployment.

II. Related Work

Multimodal Sentiment Analysis (MSA) focuses on identifying individuals' emotional or sentiment states by leveraging multiple data modalities such as text, audio, and vision. In recent years, researchers have moved beyond unimodal analysis to develop multimodal systems that more accurately reflect how humans communicate. This shift has led to extensive exploration of modality fusion and representation disentanglement techniques.

A. Multimodal Fusion Strategies

Two primary paradigms exist in multimodal fusion: early fusion and late fusion. Early fusion methods merge feature representations from all modalities before classification, while late fusion predicts from each modality separately and combines results at the decision level. Early fusion generally outperforms late fusion in complex tasks like sentiment recognition due to its ability to model cross-modal interactions more directly.

Several advanced models have followed this path. Tensor Fusion Networks (TFN) combined tri-modal features using tensor operations, while MFN and MARN used gated units and attention mechanisms to integrate temporal features. MulT leveraged cross-modal transformers to establish long-range dependencies between modality pairs. Although these models capture rich multimodal relationships, they struggle with modality heterogeneity — differences in feature space, scale, and semantic alignment — which can reduce performance when directly fusing features.

B. Disentangled Representation Learning

To address modality heterogeneity, recent research introduced disentangled representation learning, which separates each modality's feature space into modality-common and modality-specific components. The former captures shared semantics (e.g., rhythm, timing), while the latter retains unique, modality-exclusive features (e.g., color in vision, pitch in audio). This decomposition enables more robust fusion by focusing on aligned content across modalities.

Popular disentanglement strategies include subspace learning, adversarial learning, and transfer learning. MISA, for example, uses similarity, orthogonality, and reconstruction losses to guide separate encoders for common and specific subspaces. Other models adopt the text modality as an anchor—given its semantic richness—and attempt to align or transfer audio and visual features toward textual representations using sequence-to-sequence models or transformers.

Despite their effectiveness, these methods often rely on strict loss constraints or complex learning schemes that can lead to training difficulties and limited generalization. Moreover, specific features often contain task-irrelevant information, making their contribution to the final fused representation less reliable.

C. Attention-Based Improvements

Instead of relying on complex constraints or reinforcement-based policy models to mine complementary features, our approach introduces a parameter-free decoupling module and an attention-based fusion framework. The decoupling module uses temporal semantic similarity scores to separate common and specific features without additional training objectives or structural overhead.

We further employ cross-modal attention mechanisms to align and enhance modality-common features while selectively integrating relevant modality-specific cues. This attention-guided fusion allows the model to dynamically focus on informative parts across modalities without relying on act-reward feedback or policy optimization.

Our design achieves high performance with fewer assumptions, better interpretability, and simpler training, making it more adaptable to real-world multimodal sentiment analysis scenarios.

III. Multi-Modality Collaborative Learning (MMCL)

A. Model Overview

As shown in Fig. 1, the system receives three input modalities: visual X_v, audio X_a, and text X_t. Each is projected into a unified latent space, resulting in representations $Z_v, Z_a, Z_t \in R^{L \times d_k}$, where L is the sequence length and d_k is the feature dimension.

Our approach aims to extract collaborative features across modalities by dividing them into:

- **Modality-common features:** shared emotional signals (e.g., rhythm)
- **Modality-specific features:** unique signals (e.g., facial color or audio tone)

We use a parameter-free Common-Specific Decoupling (CSD) module to achieve this separation. Then, we apply self-attention to highlight important common features and cross-modal attention to fuse both common and specific components into a final representation used for sentiment classification.

B. Common-Specific Representation Decoupling (CSD)

To avoid complex models, our decoupling strategy relies on semantic similarity scores between temporal segments across modalities. For example, to decouple visual features Z_v, we compute similarity matrices with audio and text features:

$$\text{Sim}_{va} = \frac{Z_v Z_a^T}{\|Z_v\| \|Z_a\|}, \quad \text{Sim}_{vt} = \frac{Z_v Z_t^T}{\|Z_v\| \|Z_t\|}$$

A comparison function F_{vs} aggregates these into a matrix W_v^c marking common features:

$$(W_v^c)_{ij} = \min(\text{Sim}_{va_{ij}}, \text{Sim}_{vt_{ij}})$$

Then:

$$Z_v^c = W_v^c \cdot Z_v, \quad Z_v^s = (1 - W_v^c) \cdot Z_v$$

This is repeated for audio and text to yield Z_a^c, Z_a^s and Z_t^c, Z_t^s.

C. Crucial Common Feature Enhancement

To emphasize informative common features, we apply intra-modal self-attention followed by a feed-forward layer and residual connection:

$$\tilde{Z}_v^c = \text{SelfAttn}(Z_v^c) + \text{FF}(Z_v^c)$$

The same is applied to Z_a^c and Z_t^c.

D. Complementary Specific Feature Integration

We use cross-modal attention between specific and common features to align and integrate relevant cues:

$$\tilde{Z}_v = \text{CrossAttn}(\tilde{Z}_v^c, Z_v^s) \tag{1}$$

$$\tilde{Z}_a = \text{CrossAttn}(\tilde{Z}_a^c, Z_a^s) \tag{2}$$

$$\tilde{Z}_t = \text{CrossAttn}(\tilde{Z}_t^c, Z_t^s) \tag{3}$$

The final joint representation is:

$$Z = [\tilde{Z}_v, \tilde{Z}_a, \tilde{Z}_t]$$

This is used for classification using a softmax layer and cross-entropy loss.

E. Final Objective

Our model is trained end-to-end with the combined loss:

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda \mathcal{L}_{\text{CL}}$$

Where $\mathcal{L}_{\text{CE}}$ is classification loss, and $\mathcal{L}_{\text{CL}}$ is contrastive loss to align modality-common embeddings.

F. Ablation Study Summary

We validate each module through ablation studies:

IV. Benchmarks and Evaluation Metrics

A. Datasets and Tasks

We evaluate our simplified MMCL framework on three key tasks: Multimodal Sentiment Analysis (MSA), Multimodal Emotion Recognition (MER), and Multimodal Depression Assessment (MDA), using four widely recognized datasets.

- **CMU-MOSI and CMU-MOSEI** are benchmark datasets for sentiment analysis. MOSI contains 1,281 training, 229 validation, and 685 testing utterances, labeled with sentiment scores ranging from –3 (strongly negative) to +3 (strongly positive). MOSEI contains over 16,000 utterances for training, 1,869 for validation, and 4,643 for testing.
- **IEMOCAP** is used for emotion recognition. We follow the standard 4-class setup (happy, sad, angry, neutral) with around 10K utterances collected from dyadic sessions.
- **CMDC** is a multimodal depression detection dataset, containing recordings of 78 subjects with PHQ-9 scores (0–27). We use 5-fold cross-validation and divide subjects based on a clinical threshold score of 9.

B. Evaluation Metrics

For MSA, we report:

- Mean Absolute Error (MAE)
- Correlation (Corr) between predictions and ground truth
- Acc2 (Binary Accuracy) using sentiment polarity
- Acc7 (7-class accuracy)
- Weighted F1-score

For MER, we report:

- Per-class and average Accuracy
- Per-class and average F1-score

For MDA, we use:

- MAE, RMSE (Root Mean Square Error)
- Pearson correlation
- Precision, Recall, and F1-score for depression classification

C. Implementation Details

We extract pretrained representations from publicly available toolkits:

- **Text:** For CMU-MOSI, MOSEI, and CMDC, we use BERT-based 768-dimensional embeddings. For IEMOCAP, we use 768-dimensional GloVe embeddings.
- **Audio:** We extract 74-dimensional COVAREP features including MFCCs, pitch, and spectral descriptors.
- **Video:** OpenFace is used to extract facial landmarks and expressions (35–47 dimensions depending on the dataset).
- **For CMDC:** we use BERT (768D), TimesFormer (768D), and VGGish (128D) features.

All modality features are projected into a 256-dimensional latent space and fused via either weighted summation or concatenation.

D. Training Configuration

- Optimizer: Adam
- Learning Rate: 0.0003
- Batch sizes: 64 (MSA), 128 (MER and MDA)
- Epochs: 200
- Hardware: NVIDIA 2080Ti GPU

Unlike the original MMCL which relied on policy-reward structures, our approach uses parameter-free semantic decoupling, self-attention, and cross-modal attention, enabling end-to-end training with a single cross-entropy objective and optional contrastive loss.

V. Conclusion

In this paper, we present a simplified and interpretable approach for multimodal sentiment analysis by capturing enhanced and complementary collaborative features across text, audio, and visual modalities. Our improved MMCL model first employs a parameter-free semantic decoupling module to separate unimodal features into modality-common and modality-specific components.

To better utilize these components, we enhance common features using intra-modal attention and integrate modality-specific cues through cross-modal attention, eliminating the

TABLE I
ABLATION STUDY RESULTS

Setting	IEMOCAP Acc	F1	MOSI Acc7	Acc2	F1	MAE	Corr
Full	84.9	84.5	50.4	87.3	87.3	0.672	0.817
w/o CSD	81.9	81.2	47.0	85.7	85.6	0.714	0.804
w/o Self-Attn	83.1	82.4	47.2	85.7	85.6	0.701	0.806
w/o Cross-Attn	82.7	81.6	47.5	85.3	85.1	0.707	0.799

need for complex reinforcement learning mechanisms or policy-reward structures. This design improves training stability, interpretability, and performance.

Extensive experiments on benchmark datasets such as IEMOCAP, CMU-MOSI, MOSEI, and CMDC demonstrate the effectiveness of our approach. The attention-based fusion not only outperforms previous methods but also adaptively emphasizes informative features without introducing additional training complexity. Our findings confirm that collaborative feature extraction through decoupling and attention-based fusion is both practical and powerful for real-world multimodal sentiment analysis applications.

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