LEARNING HOLISTIC-COMPONENTIAL PROMPT GROUPS FOR MICRO-EXPRESSION RECOGNITION

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ABSTRACT

Micro-expressions (MEs) are facial muscle movements that reveal genuine underlying emotions. Due to their subtlety and visual similarity, micro-expression recognition (MER) presents significant challenges. Existing methods mainly rely on low-level visual features and lack an understanding of high-level semantics, making it difficult to differentiate fine-grained emotional categories effectively. Facial action units (AUs) provide local action region encodings, which help establish associations between emotional semantics and action semantics. However, the complex cross-mapping relationship between emotional categories and AUs easily leads to semantic confusion. To address these problems, we propose a novel framework for MER, called HCP_MER, which leverages the powerful alignment capabilities of visual-language models such as CLIP to construct multi-modal visual-language alignments through holistic-componential prompt groups. We provide corresponding holistic emotion and componential AU prompts for each emotion category to eliminate semantic ambiguity. By aligning optical flow and motion magnification representations with componential and holistic prompts, respectively, our approach establishes multi-granularity complementary visual-semantic associations. To ensure the precise attribution of predicted emotional semantics, we design a consistency constraint to enhance decision stability. Finally, we integrate adaptive gated fusion of complementary responses with downstream supervisory signal optimization to achieve fine-grained emotion discrimination. Experimental results on CASME II, SAMM, SMIC, and CAS(ME)^3 demonstrate that HCP_MER achieves competitive performance, exhibiting remarkable robustness and discriminability.

1 INTRODUCTION

Micro-expressions (MEs), which are brief and subtle facial movements produced when humans suppress their true emotions, have significant applications in fields such as clinical psychological diagnosis, security screening, and intelligent human-computer interaction (Oh et al., 2018b). Their extremely short duration, low-intensity localized muscle changes, and highly similar visual patterns together pose the core challenge in micro-expression recognition (MER) (Ekman & Friesen, 1969; Shen et al., 2012; Svetieva & Frank, 2016). Existing methods primarily rely on convolutional neural networks (CNNs) to extract visual features from facial images (Zhang et al., 2018b; Tran et al., 2021) or use graph neural networks (GNNs) to model facial structural information (Lei et al., 2020), achieving impressive performance. However, these approaches are limited to low-level visual features and lack the ability to understand higher-level emotional semantics, making it difficult for them to achieve fine-grained classification in emotional categories with highly similar visual features.

Recently, visual-language large models (such as CLIP (Radford et al., 2021)) have mapped images and text into a shared semantic space through large-scale contrastive learning, enabling the visual encoder to perceive rich cross-modal semantic information, which has opened up new research avenues for MER. However, the original CLIP's rigid template description "a photo of [class]" is poorly suited to capture the subtle local features of MEs. In response, Liu et al. (2025b), leveraging facial anatomical knowledge, constructed fine-grained textual prompts through facial action units (AUs) encoding (Prince et al., 2015), significantly enhancing CLIP's ability to perceive local movements of MEs. Yet, different emotional categories of MEs may activate similar AU combinations

(as shown in Appendix A), which suggests that a single AU-based alignment strategy is insufficient to maintain sensitivity to fine-grained emotional differences.

While we acknowledge the success of previous approaches, we propose to rethink the use of single fine-grained textual prompts. The core insight is that emotional categories in a single prompt's semantic space may risk cross-contamination, and the key to MER lies in capturing both the component semantics that reveal subtle movements and the overall semantics that convey the general emotion.

Inspired by this fact, we propose a multimodal visual-language alignment framework for MER, called HCP_MER, which is constructed with holistic-componential prompt groups (HCP Groups). Specifically, we construct a one-to-one corresponding holistic-component prompt group for each emotional category, where the holistic prompt describes the macro emotional state, and the component prompt refines the corresponding AU combinations. This binding design addresses the complex mapping relationship between emotion and AUs, thus eliminating semantic ambiguity in single prompts. Additionally, we design a multimodal visual-language alignment: aligning the enlarged full-face image features with the holistic prompt and aligning optical flow features with the component prompt. By establishing multi-granularity complementary visual-semantic associations, we further enhance the model's sensitivity to fine-grained emotional discrimination. Furthermore, we introduce a lightweight Adapter after the visual encoder to improve cross-modal alignment quality and effectively mitigate the overfitting risk caused by the scarcity of ME data. To ensure the accurate attribution of predicted emotional semantics, we design a consistency constraint to enhance decision stability. Finally, by combining adaptive gated fusion of complementary responses and downstream supervision signal optimization, HCP_MER achieves fine-grained and robust emotional discrimination.

2 Related work

MER Methods. In early studies, researchers primarily relied on handcrafted feature extractors to capture facial expression variations across spatial and temporal dimensions. Methods such as Pfister et al. (2011) and Wang et al. (2014) were widely used to model video sequences but incurred significant computational overhead. To address this, Davison et al. (2018) proposed a novel approach that performs recognition based only on the apex and onset frames. By combining local optical flow magnitudes with global optical strain through a dual-weighting mechanism, their method effectively enhanced feature representation. However, traditional feature engineering methods, due to their inherently linear nature, struggle to capture the nonlinear and localized motion patterns characteristic of MEs. This limitation has driven the community towards deep learning frameworks, which can learn more discriminative representations. For instance, Gan et al. (2019) and Van Quang et al. (2019) utilized apex frames and optical flow to extract structurally aware features through convolutional or capsule-based architectures, improving responsiveness to subtle facial movements. Subsequently, recurrent convolutional networks (Xia et al., 2020) introduced temporal dependencies across frames to better capture ME evolution. Moreover, the incorporation of Transformer modules has further improved the modeling of subtle movements in key facial muscle regions (Wang et al., 2024). More recently, methods such as Micro-BERT (Nguyen et al., 2023) and SelfME (Fan et al., 2023) adopted self-supervised paradigms, enabling models to inherently learn to capture the fine-grained dynamics of MEs, thus further improving classification performance.

Vision-Language Model. In parallel, vision-language models (VLMs) have garnered increasing attention due to their powerful multimodal semantic alignment and transfer capabilities. CLIP (Radford et al., 2021), a prominent model in this domain, maps images and text into a shared semantic space through large-scale contrastive learning on image-text pairs, achieving impressive zero-shot generalization. To enhance CLIP's adaptability to specific tasks, Zhou et al. (2022b) proposed learnable contextual prompt vectors, enabling efficient few-shot transfer without fine-tuning the backbone network. Zhou et al. (2022a) further introduced a conditional context optimization mechanism, allowing prompts to dynamically adjust based on image features to mitigate class distribution shifts. Subsequent works, such as (Gao et al., 2024) and (Tian et al., 2024), employed feature adapters and attribute-guided mechanisms to improve CLIP's performance in downstream tasks. Khattak et al. (2023) advanced this line of research by designing shared and modality-specific prompt structures and incorporating multi-layer cooperative alignment across visual and textual branches, significantly

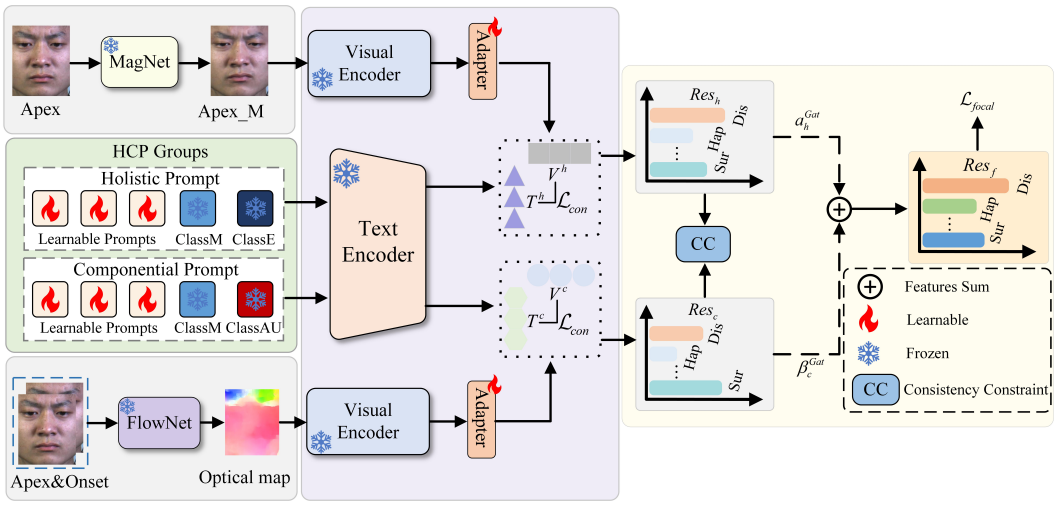


Figure 1: The overall architecture of HCP_MER. Gray blocks indicate visual inputs (Apex_M and the optical map), green blocks denote textual inputs (HCP Groups), purple blocks represent multimodal vision–language alignment, and yellow blocks perform consistency constraints with adaptive gated fusion. Dashed boxes explain the key symbols.

improving cross-modal consistency. In the context of facial expression recognition (FER), Ma et al. (2025) introduced a hierarchical prompt generator and a soft-hard prompt alignment strategy, which effectively alleviated semantic mismatches across modalities and led to notable improvements in cross-dataset emotion recognition. Although VLMs have demonstrated promising results in general vision tasks and FER, their application to MER is still in its early stages. As a pioneering work, Liu et al. (2025b) encoded facial AUs into semantic prompts and aligned them with CLIP's visual representations, enabling the model to learn more discriminative ME features. This work demonstrated the potential of VLMs in MER tasks. However, a key challenge remains in effectively utilizing language prompts to model the complex mappings between AUs and emotional categories.

3 Proposed Methodology

3.1 Overview

We propose a novel MER method, HCP_MER, whose overall framework is shown in Fig. 1. First, we construct HCP Groups, effectively addressing the emotional semantic ambiguity caused by a single AU by establishing a binding holistic-componential semantic context. Next, we design a multimodal visual-language alignment mechanism, enhancing the model's sensitivity to fine-grained emotional differences by establishing multi-granularity complementary visual-semantic associations. Furthermore, inspired by the concept of mutual distillation, we introduce a consistency constraint between the holistic and component responses to ensure stable emotional category attribution. Finally, we combine adaptive gated networks to fuse complementary responses and optimize downstream supervision signals, enabling HCP_MER to achieve fine-grained and robust emotional discrimination.

3.2 HCP Groups

Previous coarse-grained textual prompts, such as "a photo of [class]", are insufficient for accurately distinguishing ME categories. While AU units, as used in MER_CLIP (Liu et al., 2025b), can refine textual prompts, the cross-mapping relationships between different emotional categories and their corresponding AU encodings complicate the model's understanding of emotional semantics. To address this issue, we attempt a method to extend the dimensionality of textual prompts to resolve the semantic crossover under single prompts. Specifically, we build upon the existing textual

prompt framework and incorporate ideas from COOP (Zhou et al., 2022b) to make the text templates learnable, assisting CLIP in better adapting to various downstream tasks. We define CLASSM as a unified category referring to MEs. However, a single CLASSM textual prompt still fails to meet the requirements for fine-grained ME classification. To address this, we adopt the attribute-guided prompt adjustment strategy from the ArGue (Tian et al., 2024) method, incorporating specific visual attributes for different ME categories to further refine the textual prompts. In the holistic prompt, we introduce CLASSE as an indicator for emotional categories, clearly marking the macro emotional state of the facial expression, enabling the model to perceive the overall emotion. In the componential prompt, we introduce CLASSAU, which represents the specific AU unit combinations for the corresponding ME category, encoding the motion regions of the ME. Combining the CLIP tokenizer, we obtain the learnable contextual tokens $[l_1, l_2, \ldots, l_k]$ and the CLASS token T_c, which together construct the holistic and componential prompt sequences P_h and P_c (the full token sequence construction details are provided in Appendix B).

Through this design, a one-to-one correspondence is established between holistic prompts and componential prompts, organized into HCP Groups. The holistic prompts provide semantic context for the componential AUs, helping to distinguish similar AU combinations, while the componential prompts offer fine-grained information for the overall emotion, accommodating the diverse manifestations of the same emotion and avoiding semantic crossovers between different emotional categories.

3.3 Multimodal Visual-Language Alignment

We know that the original CLIP uses the entire image as the visual feature input. Although this performs excellently on natural datasets such as ImageNet, MEs exhibit highly similar facial backgrounds and extremely low motion intensity, causing the visual features to show high similarity, which reduces the model's discriminative sensitivity. Furthermore, directly fine-tuning the entire visual encoder would inevitably disrupt the original pre-trained knowledge while also facing severe overfitting risks due to the scarcity of ME data.

To address this, we propose Multimodal Visual-Language Alignment. In terms of visual input, we use the classic MagNet magnification algorithm (Oh et al., 2018a) to obtain the motion-magnified apex frame (Apex_M), which helps highlight the muscle changes occurring during MEs. Simultaneously, the optical flow estimation algorithm, FlowNet (Ilg et al., 2017), computes the motion information between the starting frame and the apex frame, generating an optical flow map to further enhance the capture of temporal motion information. This approach increases the visual saliency difference of MEs in both spatial and spatiotemporal dimensions.

We align the Apex_M visual features with the holistic emotional text description, enabling the model to construct the overall emotional semantics. Meanwhile, we align the optical flow map with the componential AU text description, forcing the model to focus on the semantics of local subtle motions. Through Multimodal Visual-Language Alignment, we establish multi-granularity complementary visual-semantic associations, further enhancing the model's sensitivity to fine-grained emotions. Moreover, to ensure efficient adaptation of MEs to CLIP and reduce the risk of model overfitting, we add a lightweight adapter after the visual encoder (detailed architecture in Appendix B), and combine cosine similarity matching with contrastive loss to further optimize the cross-modal alignment quality. The specific formula is as follows:

$$S(V,T) = \sum_{k=h,c} \frac{V^k \cdot T^k}{\|V^k\|\|T^k\|}, \tag{1}$$

$$\mathcal{L}_{con} = -\sum_{i=h,c} \log\left(\frac{\exp(S(V^i,T^i)/\tau)}{\exp(S(V^i,T^i)/\tau) + \sum_{j\neq i}\exp(S(V^i,T^j)/\tau)}\right), \tag{2}$$

where V^k and T^k represent the holistic and componential visual features and text features, respectively. $\|V^k\|$ and $\|T^k\|$ are the norms of the visual and text features, respectively. $S(V^i,T^i)$ represents the similarity between the visual feature V^i and the text feature T^i, while $S(V^i,T^j)$

represents the similarity between different visual and text features. τ represents the temperature parameter, which is used to adjust the sensitivity of the similarity. The specific implementation details are shown in Appendix B.

3.4 CONSISTENCY CONSTRAINT

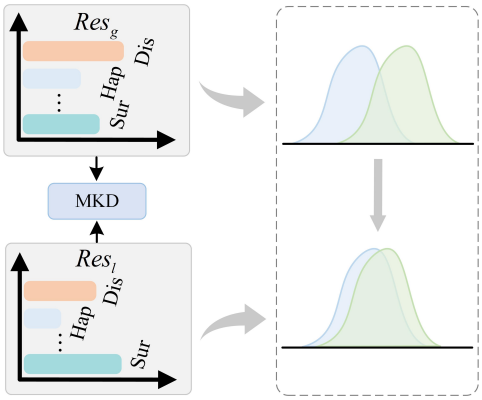


Figure 2: Illustration of the consistency constraint.

Although we have mined multi-granularity complementary visual-semantic representations, enhancing the model's sensitivity to fine-grained distinctions, the holistic and component branches are inherently based on different visual cues and textual contexts. The semantic differences between them may still lead the model to learn inconsistent emotional features, as reflected in the distribution differences between holistic response Res_h and componential response Res_c, which in turn affects the accurate attribution of emotional categories. We aim for the model to maintain sensitivity to subtle emotional differences while enhancing decision stability. To address this, we introduce a consistency constraint (CC) mechanism based on the idea of mutual knowledge distillation (MKD) (Zhang et al., 2018a), as shown in the Fig. 2.

The CC establishes a bridge between Res_h and Res_c, facilitating knowledge-sharing optimization between them, ensuring consistency in their response space distributions and avoiding semantic confusion. The specific formula is as follows:

$$\mathcal{L}_{JS} = \frac{1}{2}\left[\sum_i Res_h(i)\log\left(\frac{Res_h(i)}{Res_c(i)}\right) + \sum_i Res_c(i)\log\left(\frac{Res_c(i)}{Res_h(i)}\right)\right], \tag{3}$$

Here, $Res_h(i)$ and $Res_c(i)$ represent the holistic and componential responses for the i-th category, respectively. We treat the output probability distributions of the overall and component branches as soft labels for each other and use symmetric KL divergence as the distribution consistency measure, thereby achieving more robust emotional semantic prediction.

3.5 ADAPTIVE GATED FUSION

We introduce a gated network to adaptively fuse multi-granularity complementary response outputs, selecting the optimal information output with minimal additional parameter cost. We define the gating function to calculate the weights for the holistic and component responses, specifically as follows:

$$w^{Gat} = \sigma(W[Res_h; Res_c]) + b, \tag{4}$$

$$Res_f = a_h^{Gat} \cdot Res_h + \beta_c^{Gat} \cdot Res_c, \tag{5}$$

where $\sigma(\cdot)$ denotes the sigmoid activation function, and W and b represent the learned weight and bias. This yields the weights a_h^{Gat} and β_c^{Gat} for the holistic and component responses, respectively. After the weighted combination, the final response distribution Res_f is obtained and combined with the downstream class imbalance loss, focal loss, for supervised optimization. The weights are updated to the optimal ratio. Ultimately, HCP_MER achieves fine-grained and robust emotional discrimination, and the total loss function is composed as follows:

$$\mathcal{L}_{final} = \mathcal{L}_{con} + \lambda_1 L_{JS} + \lambda_2 L_{focal}, \tag{6}$$

where $\mathcal{L}_{con}$ represents the contrastive loss, $\mathcal{L}_{JS}$ represents the KL divergence loss, and $\mathcal{L}_{focal}$ represents the focal loss. λ_1 and λ_2 are the corresponding hyperparameters.

Table 1: Comparative experimental results for 3-class task (UF1 and UAR on the SMIC, CASME II, and SAMM Datasets).

Methods	SMIC		CASME II		SAMM	
	UF1	UAR	UF1	UAR	UF1	UAR
LBP-TOP(Pfister et al., 2011)	0.2000	0.5280	0.7026	0.7429	0.3957	0.4102
Bi-WOOF(Davison et al., 2018)	0.5727	0.5829	0.7805	0.8026	0.5211	0.5139
CapsuleNet(Van Quang et al., 2019)	0.5820	0.5877	0.7068	0.7018	0.6209	0.5989
OFF-ApexNet(Gan et al., 2019)	0.6817	0.6950	0.8764	0.8681	0.5409	0.5392
RCN(Xia et al., 2020)	0.6326	0.6441	0.8512	0.8123	0.7601	0.6715
ICE-GAN(Yu et al., 2021)	0.5727	0.5829	0.7805	0.8026	0.5211	0.5139
SLSTT(Zhang et al., 2022)	0.7240	0.7070	0.9010	0.8850	0.7150	0.6420
FeatRef(Zhou et al., 2022c)	0.7011	0.7083	0.8911	0.8873	0.7372	0.7155
ME-PLAN(Zhao et al., 2022)	0.7130	0.7260	0.8630	0.8780	0.7160	0.7420
Micro-BERT(Nguyen et al., 2023)	-	-	0.9034	0.8914	-	-
SelfME(Fan et al., 2023)	-	-	0.9078	0.9230	-	-
HTNet(Wang et al., 2024)	**0.8049**	0.7905	0.9532	0.9516	0.8131	0.8124
EMRNet(Liu et al., 2025a)	0.6509	0.6596	0.9074	0.8995	0.6782	0.6897
MER-CLIP(Liu et al., 2025b)	-	-	0.9409	0.9487	0.8321	0.8434
Ours	0.8032	**0.8146**	**0.9547**	**0.9560**	**0.8426**	**0.8593**

4 EXPERIMENTS

4.1 EXPERIMENTAL CONFIGURATION

Implementation Details. Our experiments were implemented using the PyTorch framework and trained on an NVIDIA GeForce RTX 3080ti GPU. The optimizer used was AdamW, with 300 training epochs, an initial learning rate of 1e-4, and a batch size of 16. The values of λ_1 and λ_2 are set to 0.5. For the CLIP visual encoder, we used ViT-B/32. To ensure fairness across different models and to avoid performance bias caused by individual differences among subjects, we adopted the Leave-One-Subject-Out (LOSO) cross-validation strategy for model training and evaluation.

Experimental Metrics. Considering the class imbalance in the ME datasets, accuracy as a traditional evaluation metric may not fully reflect the model's performance. Therefore, in addition to accuracy, we also introduce the unweighted F1 score (UF1) and the unweighted average recall (UAR) as supplementary experimental metrics. These are used to evaluate the effectiveness of the model, and a detailed explanation of these metrics can be found in Appendix C.

4.2 COMPARISON WITH STATE-OF-THE-ART METHODS

We conducted comparative experiments with state-of-the-art methods on the SMIC Li et al. (2013), CASME II(Yan et al., 2014), SAMM (Davison et al., 2016), and CAS(ME)^3 (Li et al., 2022) datasets. The detailed configuration of the datasets can be found in Appendix C.

Results on SMIC, CASME II, and SAMM. As shown in Tab. 1, our comparison methods include both traditional handcrafted feature-based approaches and deep learning methods. HCP_MER achieves competitive or the best performance across all three datasets. Notably, on CASME II and SAMM, our model outperforms all previous methods with UF1/UAR of **0.9547/0.9560** and **0.8426/0.8593**, respectively. On SMIC, our method achieves the highest UAR, demonstrating excellent discriminability. However, HTNet achieves the highest UF1 on SMIC, reflecting the advantages of the transformer architecture in modeling ME features. Our method, by balancing the retention of pre-trained knowledge and mitigating overfitting risks, adopts a frozen visual encoder with an adapter, which slightly limits the performance ceiling.

Table 2: Comparative experimental results for 3-class task (UF1 and UAR on the CAS(ME)^3 Dataset).

Methods	CAS(ME)^3	
	UF1	UAR
AlexNet(Zhang & Zhang, 2022)	0.2570	0.2634
RCN-A(Xia et al., 2020)	0.3928	0.3893
FearRef(Zhou et al., 2022c)	0.4930	0.3413
u-bert(Nguyen et al., 2023)	0.5604	0.6125
HTNet(Wang et al., 2024)	0.5767	0.5415
FDP(Shao et al., 2025)	0.5978	0.5784
MER-CLIP(Liu et al., 2025b)	0.7832	0.7606
Ours	**0.8052**	**0.8012**

Table 3: Comparative experimental results for 4-class and 7-class tasks (UF1 and UAR on the CAS(ME)^3 Dataset).

Methods	CAS(ME)^3			
	4-CLASS		7-CLASS	
	UF1	UAR	UF1	UAR
AlexNet(Zhang & Zhang, 2022)	0.2915	0.2910	0.1759	0.1801
SFAMNet(Liong et al., 2024)	0.4462	0.4797	0.2365	0.2373
u-bert(Nguyen et al., 2023)	0.4718	0.4913	0.3264	0.3254
ATM-GCN(Zhang et al., 2024)	0.5423	0.5330	0.4308	0.4283
MER-CLIP(Liu et al., 2025b)	0.6544	0.6242	0.4997	0.5014
Ours	**0.7168**	**0.6996**	**0.5955**	**0.6047**

Results on CAS(ME)^3. As shown in Tab. 2 and Tab. 3, we conducted extended experiments on the more challenging CAS(ME)^3 dataset. In the 3-class classification task, we achieved UF1/UAR of **0.8052/0.8012**. In the 4-class classification task, we achieved **0.7168/0.6996**. In the finest-grained 7-class classification task, we reached **0.5955/0.6047**, outperforming MER-CLIP by **+9.58%** and **+10.33%**, respectively. As the number of classes increases, the performance of traditional or single-modal methods rapidly declines. In contrast, our method endows the model with the ability to understand high-level emotional semantics and component semantics. The combination of HCP Groups effectively resolves the confusion caused by overlapping emotional and action semantics. Additionally, the multimodal visual-language alignment builds a complementary, multi-granular visual semantic relationship, while CC further enhances decision stability and adaptive gated fusion for fine-tuned response outputs. As a result, HCP_MER maintains stable and superior performance in more complex emotional spaces.

4.3 Ablation Study

We systematically evaluate the contribution of each module on the CAS(ME)^3 dataset across 3-class, 4-class, and 7-class tasks. The full model HCP_MER demonstrates excellent performance in all tasks: 3-class (UF1/UAR = **0.8052/0.8012**), 4-class (UF1/UAR = **0.7168/0.6996**), and 7-class (UF1/UAR = **0.5955/0.6247**). The ablation experiments, as shown in the Fig. 3, reveal that using only the holistic branch (w/o COM) results in a decrease of UF1 to **0.6515** in the 3-class task, indicating that the lack of local AU details severely weakens the model's ability to capture subtle movements. When only the componential branch is used (w/o HOL), UF1 drops to **0.7123**, suggesting that the absence of global emotional context leads to incomplete semantics and classification difficulties. Removing the Adapter module (w/o Adapter) causes a significant performance drop across all tasks, highlighting its key role in retaining the pre-trained knowledge from CLIP and enhancing

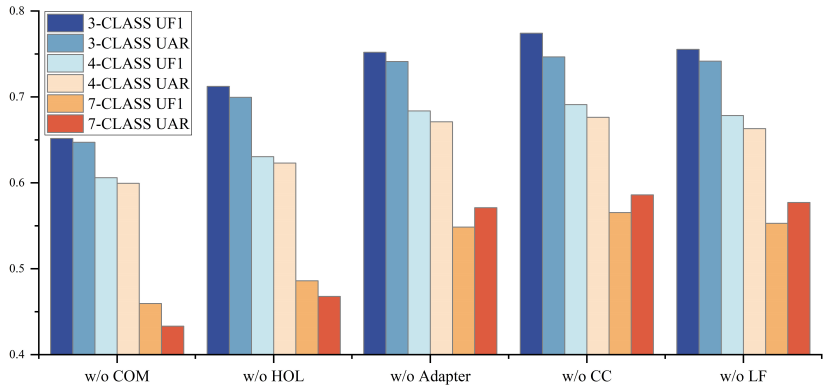


Figure 3: Ablation study on the contributions of different components in HCP_MER.

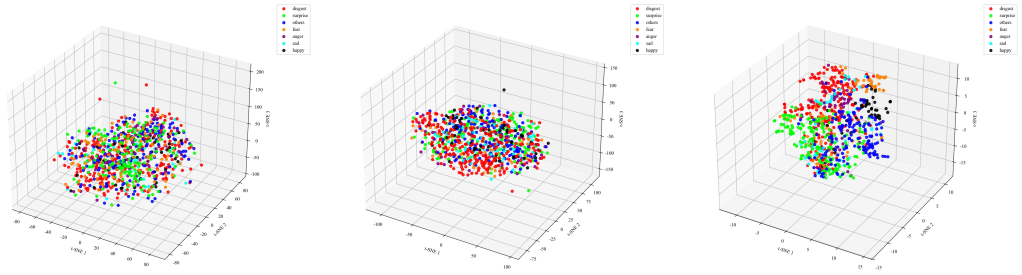
the alignment quality between the ME domain and textual semantics. Removing the Consistency Map (w/o CC) and $\mathcal{L}_{focal}$ (w/o LF) leads to decreased prediction stability and exacerbates the class imbalance problem, especially in the 7-class task. The experiments fully demonstrate that the HCP Groups and multi-visual-language alignment are the core components of HCP_MER. These modules work effectively together to enhance the model's discriminative power and robustness.

4.4 VISUALIZATION

Feature Distribution Visualization. We further employed t-SNE to analyze the feature distributions across different configurations on the 7-class task of the CAS(ME)^3 dataset. In the baseline model without the Adapter (a), the feature distribution is highly mixed, highlighting that the pre-trained CLIP weights alone are insufficient for the MER task. The adapter bridges the gap between visual and textual features, improving alignment. Adding the Adapter without CC and $\mathcal{L}_{focal}$ (LF) for decision consistency and class imbalance handling (b) improves inter-class separability, although significant overlap persists. In contrast, our proposed HCP_MER method (c) substantially enhances the feature space's geometric structure: samples from the same class form compact clusters, while those from different classes are clearly separated. The method also improves discriminability, particularly for semantically similar categories. This confirms the effectiveness of our approach in fine-grained MER, aligning with our quantitative results.

Visualization of Attention Distributions. We present a visual analysis of the attention distributions across the holistic and componential branches for various emotional samples. As shown in Fig. 5, the two branches exhibit distinctly different yet complementary attention patterns. Specifically, the holistic branch demonstrates a broad, diffuse attention distribution, typically spanning macro facial regions crucial for understanding the overall emotional context. For example, for the happy emotion, we observed that the attention covers the cheeks, eyes, and lips, which are key areas associated with the macroscopic expression of happiness. At the same time, the component branch shows highly localized and concentrated attention, focusing on specific muscle groups related to AU activations. For instance, the attention corresponding to the happy emotion is predominantly concentrated around the eyes and lips, which reflects the fine-grained componential semantics.

We observe that the attention distributions of the two branches exhibit complementary characteristics. This clear divergence in attention patterns verifies that our HCP Groups successfully guide the visual encoder to perceive semantically distinct yet complementary features. Simultaneously, the presence of overlapping attention areas indicates that the model performs collaborative observation of the same facial regions from different semantic dimensions. Based on these characteristics, the adaptive gated fusion network does not simply merge these features, but rather learns to dynamically recalibrate and assign optimal weights according to the input sample. This process is further optimized under the guidance of downstream supervisory signals, enabling the model to execute refined weight allocation between macroscopic expression context and subtle motion details, thereby achieving more accurate emotion discrimination.



(a)W/O Adapter (b) W/O CM+LF (c) Our HCP_MER

Figure 4: Feature space distribution for the 7-class classification task on CAS(ME)^3.

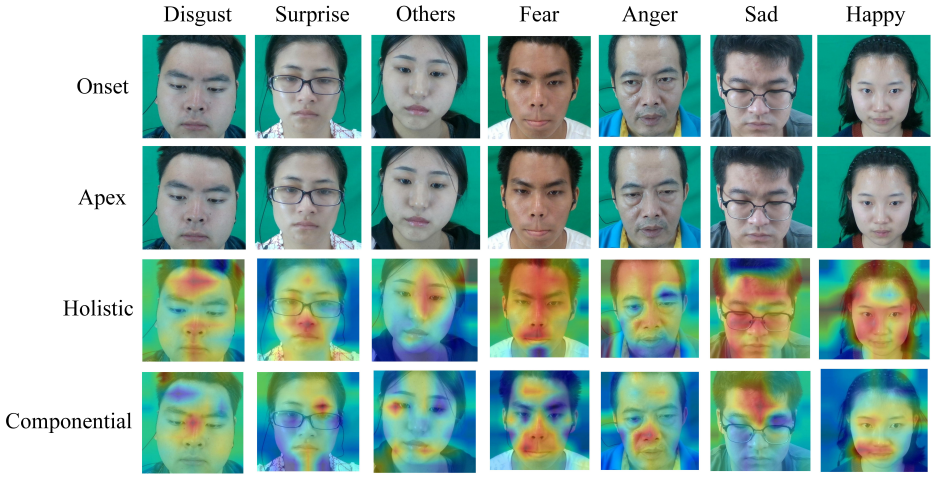


Figure 5: Attention distribution across the holistic and componential branches.

5 Conclusion

In this paper, we propose a novel MER framework, HCP-MER. We introduce the holistic-componential prompt groups, which effectively alleviate the semantic ambiguity issue by binding holistic emotional semantics with componential AUs semantics. At the same time, leveraging the powerful alignment capabilities of VLMs like CLIP, we propose a multimodal visual-language alignment approach that establishes multi-granularity complementary visual-semantic associations, enhancing the model's sensitivity to fine-grained emotional discrimination. Building on this, the consistency constraint ensures the accurate attribution of emotional predictions, while adaptive gated fusion combines complementary responses from different branches and incorporates fine-tuned optimization with downstream supervisory signals. Extensive experiments validate the superiority of our method, demonstrating the robustness and discriminative power advantages of HCP-MER. Our method provides a new research perspective for fine-grained MER based on VLMs. In the future, we will further explore the automated generation mechanism of prompts and attempt to extend it to more challenging zero-shot MER scenarios.

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APPENDIX

The appendix is structured as follows:

- Appendix A elucidates and visualizes the cross-mapping problem between emotion categories and AU units.
- Appendix B presents the implementation details of the proposed HCP Groups and Adapter.
- Appendix C provides additional information on the experimental setup and results.
- Appendix D provides details on the use of LLMs.

Figure 6: (a) Many-to-One Mapping, (b) One-to-Many Mapping.

A Cross Mapping

We examine a fundamental challenge in MER: the complex, non-injective mapping between AUs and emotion categories. This mapping underlies the semantic ambiguities faced by models that rely exclusively on AU prompts.

As shown in Fig. 6(a), a many-to-one mapping occurs when distinct emotion categories activate highly similar AU combinations. For instance, AU4 (brow lowering) is present in both anger and disgust, making it difficult for models to discriminate between these emotions based solely on this unit. In contrast, Fig. 6(b) illustrates a one-to-many mapping, where a single emotion category corresponds to multiple AU combinations under different conditions. For example, anger may manifest not only as AU4 (brow lowering), but also as AU14 (dimple formation) and other AUs. This variability further increases the likelihood of errors when inferring emotion categories solely from AU information. The schematic of the cross-mapping mechanism is depicted in Fig. 7(a), highlighting the intricate relationship between AUs and emotion categories. To mitigate this challenge, we move beyond designing independent AU prompts for each emotion. Instead, as illustrated in Fig. 7(b), we establish a one-to-one correspondence between each emotion category and a set of holistic component prompt groups. Within this framework, the holistic cues provide semantic context for differentiating similar AU combinations, while the component cues deliver fine-grained information to capture the diverse manifestations of the same emotion.

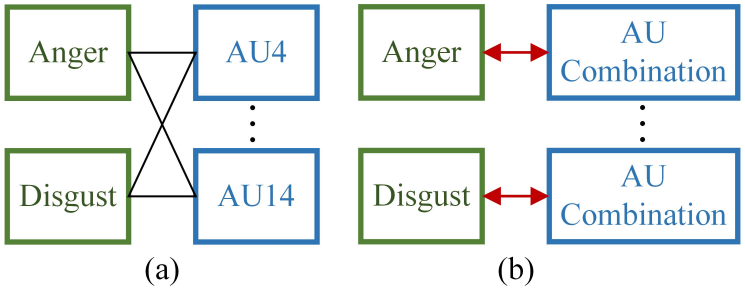


Figure 7: (a) Single AU prompting method, (b) Our proposed HCP Groups.

B Implementation Details

B.1 HCP Groups

We adopt a structured text template, *"a photo of"*, to introduce semantic priors. Inspired by the CoOp (Zhou et al., 2022b) framework and aiming to fully exploit the semantic information embedded in the word embedding space while enhancing generalization in MER, we make the template learnable. Specifically, we leverage CLIP's tokenizer to learn the entire sequence of tokens, $[l_1^h, l_2^h, \ldots, l_k^h]$, along with its component sequence counterpart $[l_1^c, l_2^c, \ldots, l_k^c]$.

The class token [CLASS] is decomposed into three semantic parts: CLASSM, representing emotion as contextual background; CLASSE, denoting emotion categories; and CLASSAU, capturing AU combinations. The tokenizer then maps [CLASS] into token representations as follows:

$$t_c = \text{tokenizer}([\text{CLASS}]). \tag{7}$$

This yields three token classes, t_c^m, t_c^e, t_c^{au}, which are integrated into the holistic and component prompt sequences P_h and P_c:

$$P_h = \left\{ l_1^h, \ldots, l_{[k/2]}^h, t_c^m, t_c^e, l_{[k/2]+1}^h, \ldots, l_k^h \right\}, \tag{8}$$

$$P_c = \left\{ l_1^c, \ldots, l_{[k/2]}^c, t_c^m, t_c^{au}, l_{[k/2]+1}^c, \ldots, l_k^c \right\}. \tag{9}$$

By inserting the token classes t_c^m, t_c^e, t_c^{au} into their designated positions, the constructed sequences are passed through the pre-trained CLIP text encoder to produce high-dimensional embeddings:

$$T^h = \tau(P_h), \quad T^c = \tau(P_c), \tag{10}$$

where τ denotes the text encoder, and T^h and T^c correspond to the holistic and componential high-dimensional semantic embedding, respectively.

Algorithm 1 HCP Groups Construction

Input: Template " a photo of ", content of [CLASS].
Output: High-dimensional embeddings T^h, T^c.
Initialize learnable structured template.
Define holistic and component prompt sequences: $P_h = [l_1^h, \ldots, l_k^h]$, $P_c = [l_1^c, \ldots, l_k^c]$.
Define class token $t_c = tokenizer$[CLASS].
Expand class token into: t_c^m, t_c^e, t_c^{au}.
Get three token classes: t_c^m, t_c^e, t_c^{au}.
for each emotion category and AU combination **do**
  Insert t_c^m, t_c^e, t_c^{au} into P_h and P_c.
  Update P_h and P_c with token classes:
  $P_h = [l_1^h, \ldots, t_c^m, t_c^e, \ldots, l_k^h]$
  $P_c = [l_1^c, \ldots, t_c^m, t_c^{au}, \ldots, l_k^c]$
  Apply CLIP tokenizer: $T^h = \tau(P_h), \quad T^c = \tau(P_c)$
end for
Return T^h, T^c

B.2 Adapter Design

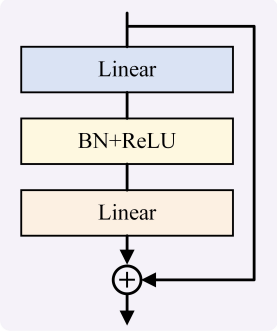


Figure 8: The design of the adapter.

To mitigate the risk of overfitting in MER, we incorporate a lightweight adapter module after the visual encoder. As illustrated in Fig. 8, the adapter follows a residual design. Specifically, the extracted features are first projected into a lower-dimensional space through a linear layer, followed by BatchNorm and a ReLU activation for normalization and nonlinear transformation. The transformed features are then restored to the original dimensionality via another linear layer, after which the input features are added back through a residual connection.

Furthermore, we adaptively adjust the adapter's complexity according to the dataset size. For smaller datasets such as CASME II (Yan et al., 2014), SAMM (Davison et al., 2016), and SMIC (Li et al., 2013), where the number of samples is limited, we employ a single adapter layer to constrain the parameter count. In contrast, for larger datasets such as CAS(ME)^3 (Li et al., 2022), we adopt a multi-layer adapter structure, which increases model capacity and enhances the quality of cross-modal alignment.

C Experimental Setup and Results

C.1 Datasets

In this paper, we conduct experiments using four publicly available ME datasets. The experiments are carried out for a 3-class classification task on the CASME II Yan et al. (2014), SMIC Li et al. (2013), and SAMM Davison et al. (2016) datasets, while for the CAS(ME)^3 Li et al. (2022) dataset, we perform 3-class, 4-class, and 7-class classification experiments. Tab. 4 and Tab. 5 will present the sample sizes for each class in the different datasets.

The CASME II dataset consists of data from 26 subjects, with a total of 255 samples. All samples were captured in a laboratory setting with a camera at 200 fps and a resolution of 640 × 480 pixels. The samples span seven emotion categories: happiness, surprise, disgust, sadness, fear, repression, and others. We conducted 3-class experiments on this dataset.

The SMIC dataset includes three subsets captured by different types of cameras: HS (high-speed camera), VIS (visual spectrum camera), and NIR (near-infrared camera). As high-speed cameras can effectively capture the subtle and transient changes of MEs, we selected the HS subset for our experiments. This subset contains data from 16 subjects, recorded at 100 fps with a resolution of 640 × 480 pixels, and includes three emotions: positive, negative, and surprise. We conducted 3-class experiments on this subset.

The SAMM dataset includes data from 28 subjects, with a total of 159 samples. All samples were recorded using high-speed cameras with a frame rate of 200 fps and a resolution of 2040 × 1088 pixels. This dataset contains eight emotions, including happiness, contempt, disgust, surprise, fear, anger, sadness, and others. We conducted 3-class experiments on this dataset.

The CAS(ME)^3 dataset contains spontaneous ME videos from 216 subjects, divided into three parts: Part A includes 1,300 videos (943 MEs and 3,143 macro-expressions); Part B consists of 1,508 unlabeled videos; and Part C contains simulated crime scenario videos with high ecological validity (166 MEs and 347 macro-expressions). The dataset covers seven emotion categories: happiness, disgust, fear, anger, sadness, surprise, and others. We mainly used Part A's ME samples to conduct 7-class, 4-class, and 3-class experiments.

Table 4: Number of Samples per Class for the 3-Class Task on SMIC, CASME II, and SAMM

SMIC		**CASME II**		**SAMM**	
Class	**Num**	**Class**	**Num**	**Class**	**Num**
Positive	51	Positive	32	Positive	26
Negative	70	Negative	90	Negative	92
Surprise	43	Surprise	25	Surprise	15

Table 5: Number of Samples per Class in the 3-class, 4-class, and 7-class Tasks on CAS(ME)^3

	CAS(ME)^3	
	Class	**Num**
3-class	Positive	57
	Negative	457
	Surprise	187
4-class	Negative	457
	Positive	57
	Surprise	187
	Others	161
7-class	Disgust	250
	Fear	86
	Anger	64
	Sad	57
	Happy	57
	Surprise	187
	Others	161

C.2 Evaluation Metrics

In this paper, we adopt three standard metrics for MER: Accuracy, Unweighted F1-score (UF1), and Unweighted Average Recall (UAR). Their formulations are given below:

$$\text{Accuracy} = \frac{\sum_{i=1}^{C} TP_i}{N} \tag{11}$$

$$UF1 = \frac{1}{C}\sum_{i=1}^{C}\frac{2 \times TP_i}{2 \times TP_i + FP_i + FN_i} \tag{12}$$

$$UAR = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_i}{TP_i + FN_i} \tag{13}$$

where C denotes the total number of classes, N denotes the total number of samples, TP_i represents the number of samples in the i-th class that are correctly predicted, FP_i represents the number of samples that are incorrectly predicted as the i-th class, and FN_i represents the number of samples in the i-th class that are incorrectly predicted as other classes.

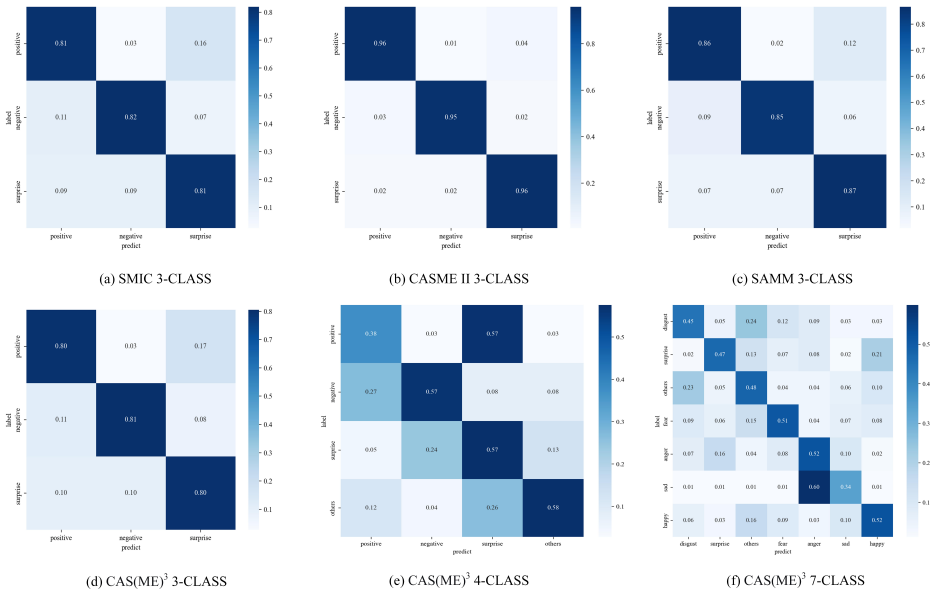
C.3 Additional Results

To provide a more comprehensive evaluation of our method, we present the confusion matrices on several public ME datasets, including SMIC (Li et al., 2013), CASME II (Yan et al., 2014), SAMM (Davison et al., 2016), and CAS(ME)^3 (Li et al., 2022), as illustrated in Fig.9. In the 3-class tasks on SMIC, CASME II, SAMM, and CAS(ME)^3, our approach yields a high proportion of correct predictions along the diagonal, indicating strong discriminative capability. Notably, CASME II and SAMM exhibit particularly stable performance, though some confusion remains between the negative and surprise categories.

For the 4-class task on CAS(ME)^3, the model achieves higher accuracy on the negative and surprise categories, while the others category proves more challenging due to their inherent diversity. In the 7-class task on CAS(ME)^3, the model demonstrates relatively strong recognition of disgust and surprise, whereas fear, happy, and sadness are more frequently misclassified. This reflects the greater

difficulty of distinguishing fine-grained emotions under conditions of sample imbalance and subtle inter-class variations.

Overall, these results not only confirm the effectiveness of HCP_MER across diverse datasets and task settings but also highlight its strong capability in discriminating emotions within complex contextual scenarios.



(a) SMIC 3-CLASS (b) CASME II 3-CLASS (c) SAMM 3-CLASS

(d) CAS(ME)^3 3-CLASS (e) CAS(ME)^3 4-CLASS (f) CAS(ME)^3 7-CLASS

Figure 9: Confusion matrices across multiple datasets and tasks.

D THE USE OF LLMS

D.1 USE OF LLMS IN RELATED WORK

We used LLMs to help search for relevant literature, in order to better evaluate prior methods and compare them with our work.

D.2 USE OF LLMS IN WRITING

We used LLMs for translation and writing refinement so that the wording of our paper would be more standardized and appropriate.