Multimodal Interactive Fusion for Action Anticipation

Zongnan Ma School of Physics and Electronic Yan'an University Shaanxi, China Email: mazongnan@yau.edu.cn Zhixiong Nan College of Computer Science Chongqing University Chongqing, China Email: nanzx@cqu.edu.cn Fuchun Zhang School of Physics and Electronic Yan'an University Shaanxi, China Email: yadxzfc@yau.edu.cn

Abstract—Action anticipation is targeted to estimate the correct verb-noun that describes a human's intended movements (verb) and objects (noun) in the future from the hundreds of possible verb-noun combinations. Different from existing methods using commonly-used fusion mechanisms (e.g., early fusion, late fusion and hybrid fusion) or transformer-based fusion mechanism (i.e., assigning a certain modal feature as query and other modal features as key and value) to fuse multimodal features, this paper for the first time proposes the Multi-round Interactive Fusion (MIF) mechanism for action anticipation. Specifically, we propose two kinds of MIF mechanisms, namely Parallel MIF and Progressive MIF. Parallel MIF treats each modal feature equally and each modal feature is alternately to be assigned as the query. Progressive MIF firstly fuses the features conveying the static information (i.e., scene and object features), and then combines the dynamic information (i.e., optical flow) to generate the final feature. Benefitting from the proposed MIF, our model outperforms state-of-the-art methods by large margins on two public datasets, achieving 14.07% action accuracy improvement on the EGTEA dataset compared with recently proposed AFFT model.

I. INTRODUCTION

With the rapid development of artificial intelligence technologies, anticipating human intentions has become crucial in many fields. Human actions[4, 5, 17], human attention [13, 14, 15] and intention objects [3, 10] are manifestations of human intent. In this paper, the focus is primarily on exploring human actions (as illustrated in Figure 1). However, human actions exhibit the great diversity and can be influenced by various factors. This complexity demands prediction models capable of dealing with uncertainty and possessing high generalization abilities. Moreover, human actions exhibit complex time dependence, requiring models to consider more contextual information.

To accurately anticipate actions, researchers have proposed a number of methods [4, 5, 8, 9, 12, 17, 19]. They typically fuse three modes of data: RGB, optical flow (FLOW) and object (OBJ). The fusion of multimodal data improves the prediction ability for several reasons: Multimodal fusion provides a more comprehensive perspective by capturing relationships among scenes, objects and motions, which helps to better understand the contextual information of actions. Although these methods have achieved some success, there are still limitations. Currently, the main fusion methods used are *early fusion, late fusion* and *hybird fusion*, they are relatively simple



Fig. 1. The action anticipation task predicts the next action based on the observed frames. Anticipation time τ_a is how much in advance the action has to be anticipated.

and rough. *Early fusion* can learn to exploit the correlation and interactions between low-level features of each modality. *Late fusion* refers to a method in which a model is trained on different modalities and then the outputs are fused [1]. *Hybrid fusion* combine *early fusion* and *late fusion*, integrating the advantages of *early fusion* to capture feature relationships and *late fusion* to handle overfitting [21], but also increases the training difficulty of the model. As a result, models produced by these fusion methods have some obvious shortcomings, including: 1) inadequate processing of multimodal data leading to characteristic information loss and repetition, 2) insufficient correlation modeling to capture complex relationships across modalities and 3) lack of flexibility and adaptability affects the robustness and reliability of models.

Therefore, this paper proposes a *Multi-round Interactive Fusion (MIF)* model to address the aforementioned shortcomings. *MIF* utilizes interactions between different modalities to facilitate information exchange and integration, providing a better way to capture semantic information and relationships across modalities. Furthermore, it improves the efficiency of data training and information mining. We explore two different interactive fusion methods. One is the parallel interactive fusion, and the other is progressive interactive fusion. Each has its own advantages. To verify the validity of our model, we compare our *Parallel MIF* and *Progressive MIF* with existing methods on EPIC-Kitchens [2] and EGTEA Gaze+[11]. The experimental results show that the two proposed fusion methods achieve significant performance improvement in action anticipation.

The main contributions of this paper are as follows: 1) we propose two kinds of *MIF* mechanisms, both of them



Fig. 2. The structure of Multi-round Interactive Fusion (MIF).

can effectively integrate information from different modes and achieve accurate action prediction, 2) we explore the combination of different modal features and verify the influence of various combinations on the model performance, this could help other researchers make more effective decisions and design models when dealing with similar problems and 3) our model has simple structure and high precision.

II. METHOD

A. Stage 1 Single modality feature strengthen

The modal features contain different information. Directly fusing information from these modalities may cause confusion or information loss, so it is necessary to first strengthen singlemodality features before fusion. Therefore, we independently calculate attention for each modality to maintain distinct information between each modality. For this aim, we propose the dual positional embedding self-attention ($\mathcal{D}PES$) module, which embeds the positions twice and it can maintain distinct information to enhance the model's timing processing ability. Stage 1 consists of three DPES, and it can be represented by the following formula:

$$F_i = \mathcal{D}PES(X_i) \text{ where } i = r, o, f \tag{1}$$

The inputs X_i represent the initial features of modality *i*. The outputs F_i are the features processed by DPES. r, o, f stand for RGB, OBJ and FLOW, respectively. In the DPES module, the computation of $\mathcal{M}HSA$ follows its original authors [18].

B. Stage 2 Parallel MIF

The existing modal fusion methods ignore the differences and correlations between different modalities, this may result in missing information and redundant information in the model. Therefore, we propose two MIF mechanisms. In this section, we first introduce *Parallel MIF* (as illustrated in Figure 2), which assign equal status to the three modalities, enabling them to take turns providing query and attending to the information from each modality. The bidirectional correlation structures of Parallel MIF can make the model better learn the relationships between two modalities and has the ability of error correction because each group in Stage 2 exhibits bidirectional correlation. If an error occurs in one direction, the other direction can be corrected. For instance, in the two $\mathcal{D}MF$ modules of *Group R-O*, the roles of F_o , and F_r are reversed.

 $\mathcal{D}MF$ is based on multi-head cross-attention ($\mathcal{M}HCA$). We fuse the two modalities in such a way that one modal features provide query to $\mathcal{M}HCA$ while the other modal features provide key and value. The inputs and outputs of $\mathcal{M}HCA$ are given by the following formula:

$$F_{ij} = \mathcal{M}HCA(F_i, F_j) \text{ where } i, j \in \{r, o, f\} \text{ and } i \neq j$$
(2)

where F_{ij} are the fusion features of modalities *i* and *j*. F_i provide Q, F_j provide K and V. The calculation of $\mathcal{M}HCA$ is similar to $\mathcal{M}HSA$, except that the providers of Q, K, and V features are not the same.

After obtained the outputs F_{ij} of MHCA, we add residual and LayerNorm to it to get the outputs F'_{ij} of $\mathcal{D}MF$.

$$\mathcal{D}MF(F_i, F_j) = LN(F_{ij} + F_i) = F'_{ij}$$
 (3)
Finally we sum the outputs of the six $\mathcal{D}MF$ modules to get the final value:

$$F_s = \sum F'_{ij} \tag{4}$$

The *Parallel MIF* has a bidirectional error correction ability, resulting in strong robustness. It can adapt well to different datasets and does not require us to consider which modal data has a strong modal correlation.

C. Optional Stage 2 Progressive MIF

We provide an Optional Stage 2 Progressive MIF, which can replace Stage 2. Parallel MIF and Progressive MIF have their own advantages. Parallel MIF is more robust and less thoughtful. Progressive MIF is more flexible and can achieve higher precision.

In this stage, we take into account the differences among each modality and assign different weights to the information they provide. Firstly, we fuse the static features F_r and F_o by utilizing F_r as the primary source of information for the *query* and residual. During this process, F_r play the most crucial guiding roles. Then, we deploy the fused static features F_n as the query to combine dynamic features F_f . The process is as follow formula:

$$\mathcal{D}MF(F_r, F_o) = F_n \tag{5}$$
$$\mathcal{D}MF(F_r, F_f) = F_{c'} \tag{6}$$

$$DMF(F_n, F_f) = F_{s'}$$
 (6)

 TABLE I

 The comparison results with the state-of-the-art.

		EPIC-Kitchens						EGTEA Gaze+						
Method		Top-5 Acc		Ν	1.Top-5 Re	с	Ava		Top-5 Acc		Ν	1.Top-5 Re	с	Ava
	VERB	NOUN	ACT	VERB	NOUN	ACT	- Avg.	VERB	NOUN	ACT	VERB	NOUN	ACT	Avg.
ATSN[2] ECCV'2018	77.30	39.93	16.29	33.08	32.77	7.60	34.50	90.60	69.94	40.53	69.24	57.02	31.61	59.82
FN[7] WACV'2018	74.84	40.87	26.27	35.30	37.77	6.64	36.95	91.05	71.64	60.12	76.73	63.59	49.82	68.83
RULSTM[5] ICCV'2019	79.55	51.79	35.32	43.72	49.90	15.10	45.90	93.11	77.48	66.40	82.07	73.30	58.64	75.17
TAB[17] ECCV'2020	79.47	51.93	34.60	44.15	51.88	16.17	46.37	92.84	78.58	67.51	83.12	75.17	62.46	76.61
IRNN[19] TIP'2020	79.70	50.20	33.20	-	-	-	-	-	-	-	-	-	-	-
HA[9] 2021	73.94	41.29	25.18	35.87	36.39	14.64	37.89	86.06	71.46	59.89	78.90	69.89	58.22	70.74
HRO[12] CVPR'2022	81.53	54.51	37.42	45.16	51.78	17.80	48.03	-	-	71.46	-	-	-	-
Parallel MIF	80.89	57.38	39.40	47.37	57.65	17.90	50.10	96.23	88.28	79.89	90.74	85.98	75.70	86.14
P rogressive MIF	80.93	57.76	39.80	47.99	59.04	17.80	50.55	96.24	88.24	80.22	90.74	86.24	76.54	86.37

 TABLE II

 The comparison results with different fusion strategies.

	EPIC-Kitchens						EGTEA Gaze+							
Method		Top-5 Acc		Ν	I.Top-5 Re	с	Δνα		Top-5 Acc		N	1.Top-5 Re	с	Δνσ
	VERB	NOUN	ACT	VERB	NOUN	ACT	Avg.	VERB	NOUN	ACT	VERB	NOUN	ACT	Avg.
Early fusion	80.27	50.46	33.27	45.47	51.38	14.35	45.87	96.11	87.95	79.61	90.19	85.42	75.43	85.79
Late fusion	80.09	55.31	39.06	41.01	53.50	14.21	47.20	95.35	85.64	78.57	86.62	81.08	70.62	82.98
Hybrid fusion (r-o)	80.93	52.03	36.63	44.34	50.01	14.16	46.35	-	-	-	-	-	-	-
Hybrid fusion (r-f)	80.73	56.60	38.94	43.25	56.49	15.53	48.59	-	-	-	-	-	-	-
Hybrid fusion (f-o)	80.07	48.81	33.19	40.71	46.60	11.22	43.43	-	-	-	-	-	-	-
Parallel MIF	80.89	57.38	39.40	47.37	57.65	17.90	50.10	96.23	88.28	79.89	90.74	85.98	75.70	86.14
P rogressive MIF	80.93	57.76	39.80	47.99	59.04	17.80	50.55	96.24	88.24	80.22	90.74	86.24	76.54	86.37

Given that F_r and F_o are static features and possess high correlation due to both representing object-related information. After obtaining the static fused features F_n that combine rich information, we use F_n to combine dynamic features F_f and fuse them to complement each other's information.

D. Stage 3 Action anticipation

In the Stage 3 Action anticipation, the outputs are final anticipation results. The following formula serves as an example of using F_s as inputs for Stage 3.

$$F_{m} = Linear(LN(MLP(F_{s}) + F_{s}))$$
(7)

The multi-layer perceptron increases the number of trainable weights, and its hierarchical representation learning improves the model's generalization ability. Furthermore, the residual structure preserves the original information and accelerates convergence during the training process.

III. EXPERIMENTS

A. Experiment setup

Datasets. EPIC-Kitchens (EPIC) [2] is a dataset that contains 125 verb classes and 352 noun classes. EGTEA Gaze+ (EGTEA) [11] has 19 verb classes, 51 noun classes and 106 action classes. EGTEA is official split into three parts. We report the average of the three splits. For fairness, we use the pre-extracted modal features by [5] in the two datasets and conduct tests on validation sets which are split by [5].

Fusion details. EGTEA only provides two modalities: RGB and FLOW, so there are only two DMF modules in Stage 2 on EGTEA, and in the two modules, F_r and F_f take turns

to provide query. In Optional Stage 2, we use F_r provide the query of the first DMF module and the key and value of the second DMF module.

B. Comparisons to previous works

Comparisons with the state-of-the-art. We compare our model to the state-of-the-art in Table I, and the results demonstrate that our model achieves competitive performance. The anticipation time τ_a is 1s. 'Avg.' represents the average value of all metric results for each method. Most existing methods employ late fusion and do not thoroughly investigate the relationships between features from different modes. Features across these modes contain complementary information, and we integrate them interactively to obtain richer features representation and a more comprehensive understanding of the scene. Among our two methods, 'Progressive MIF' shows superior overall performance compared to 'Parallel MIF'. However, 'Parallel MIF' still has its advantages and significance. The parallel method is more robust and assigns equal importance to all modalities, eliminating the need to consider which modality should be given more weight, even when applied to other datasets.

Comparisons with different fusion strategies. To verify that interactive fusion is more effective than other fusion methods, we conducted comparisons with different fusion strategies and the results are shown in Table II. For fairness, during the comparisons, other structures of our model remained unchanged. In the table, '*Hybrid fusion (r-o)*' denotes the two features in parentheses undergoing *early fusion* and

TABLE III THE TOP-5 ACTION ACCURACY (%) RESULTS ON DIFFERENT ANTICIPATE TIME $\tau_a.$

Method		EP	IC-Kitch	ens			EG	STEA Ga	ze+	
Method	2	1.75	1.5	1.25	1	2	1.75	1.5	1.25	1
ED[6] BMVC'2017	21.53	22.22	23.20	24.78	25.75	45.03	46.22	46.86	48.36	50.22
FN[7] WACV'2018	23.47	24.07	24.68	25.66	26.27	54.06	54.94	56.75	58.34	60.12
RU-LSTM[5] ICCV'2019	29.44	30.71	32.33	33.41	35.32	56.82	59.13	61.42	63.53	66.40
SRL[16] TPAMI'2021	30.15	31.28	32.36	34.05	35.52	59.69	61.79	64.93	66.45	70.67
HRO[12] CVPR'2022	31.30	32.67	34.26	35.87	37.42	60.12	62.32	65.53	67.18	71.46
Parallel MIF	39.24	39.32	39.02	38.82	39.40	79.73	79.70	79.51	79.94	79.94
P rogressive MIF	39.58	39.58	39.28	39.26	39.80	79.90	79.91	79.87	80.15	80.22

the remaining feature being fused later. As shown in the table, our methods achieve the best results. Compared to the other methods, *MIF* is simpler and more effective. In our methods, features are fused at a higher level to capture richer semantic information compared with *early fusion*. Our methods better capture complex relationships between different modal features compared with *late fusion*, leading to improved generalization ability. And our model is not like *hybrid fusion*, where the choice of strategy and parameters has a great impact on the result.

Comparisons with different anticipation time τ_a . The results in Table III demonstrate that our model significantly outperforms existing methods for various anticipation times. Unlike previous methods, our method's action accuracy does not decrease as the anticipation time lengthens. This suggests that our model is better suited for long-term anticipation. The main reason is the complementarity of information from various modalities in interactive fusion. Interactive fusion is interactively fused at different information level, and it can make full use of multimodal information to reduce the error rate of model attention. So that they are not susceptible to the expected time, even for long-term predictions, the model's accuracy does not decline substantially.

TABLE IV The Top-1 Action Accuracy (%) results on EGTEA, τ_a is 0.5s.

Method	Top-1 Acc					
Wethod	VERB	NOUN	ACT			
AVT[8] ICCV'2021	51.70	50.30	39.80			
AFFT[20] WACV'2023	53.40	50.40	42.50			
Parallel MIF	58.36	59.00	47.99			
P rogressive MIF	58.16	59.25	48.48			

Comparisons of the top-1 action accuracy. In Table IV, we present the top-1 accuracy results at $\tau_a = 0.5$ on the EGTEA dataset, indicating that our model still has a significant advantage in top-1 action accuracy over previous methods.

C. Ablation Studies

In order to verify the rationality and effectiveness of the parallel interactive fusion structure, we conducted ablation experiments on it. Table V shows the action performance results of different multimodal parallel interactive fusion manners. F_r -Q', F_f -Q' and F_o -Q' are refer to the DMF modules in Stage 2 with only F_r , F_f and F_o provide query, respectively. 'Diff-All' means Q, K and V are different values and selected from $\{F_r, F_o, F_f\}$. One of the reasons *Parallel*

TABLE VTHE ABLATIONS OF **Parallel MIF**.

Monnor	EPIC-	Kitchens	EGTE	A Gaze+	
Walliei	Top-5 Acc M.Top-5 Rec		Top-5 Acc	M.Top-5 Rec	
F_r -Q	38.13	15.60	79.74	75.56	
F_f -Q	38.94	16.32	80.08	75.45	
F_o -Q	38.42	16.73	-	-	
Diff-All	38.70	16.45	-	-	
Parallel MIF	39.40	17.90	80.22	76.54	

MIF performs better is due to the bidirectional correlation between modes. In contrast, for ' F_i -Q' (i = r, o, f), the correlation is unidirectional, which may result in important information being ignored. The ability to correct errors may be limited. For EPIC, we have an additional reason because EPIC has three modes data. The reason is as follow: when F_r provide query, model does not explore the relationships between F_o and F_f , leading to weakened the interactive fusion of static and dynamic features. Regarding 'Diff-All', we analyze that the result of 'Diff-All' is not as good as that of our method because our method handles the correlation between the two modes independently. In 'Diff-All', query, key and value are provided from different modes, which may confuse the model when learning the relationships between modes.

 TABLE VI

 THE ABLATIONS OF *Progressive MIF* ON EPIC.

Manner	Top-5 Acc	M.Top-5 Rec
$\langle O, R \rangle \to F$	38.07	17.27
$\langle O, F \rangle \to R$	38.90	16.48
$\langle F, R \rangle \to O$	39.12	16.77
$\langle F, O \rangle \to R$	38.52	17.55
$\langle R,F\rangle \to O$	39.40	17.06
$\langle R, O \rangle \to F$	39.80	17.80

In order to verify the rationality and effectiveness of *Progressive MIF*, we conducted ablation experiments on it. Table VI presents the results of the action performance using different multimodal progressive interactive fusion manners on the EPIC. $\langle X, Y \rangle \rightarrow Z$ means in the first $\mathcal{D}MF$ module, the features of X provide *query*, the features of Y provide *key* and *value*. In the second $\mathcal{D}MF$ module, *key* and *value* obtained by Z. In Table VI, the results of $\langle R, O \rangle \rightarrow F$ are better than others. We think the advantage of this design is that F_o has stronger correlation with F_r , so learning the relationships between F_r and F_o first helps to capture more effective static information. Moreover, as F_r contains most of the relevant information, F_r are used as the *query* in the first

 $\mathcal{D}MF$ module, achieving the highest scores.

IV. CONCLUSION

In this paper, we propose two simple structured *MIF* mechanisms, *Parallel MIF* and *Progressive MIF*. The *Parallel MIF* possesses bidirectional correlation structures, which endows it with stronger robustness. In contrast, the *Progressive MIF* use static features to combine dynamic features to achieve higher accuracy. We compare our proposed methods to the state-of-the-art and other multimodal fusion methods, and the experimental results show that our proposed methods achieve superior performance on two large-scale datasets.

ACKNOWLEDGMENTS

This work is supported by the National Key Research and Development Program of China (No.2020AAA0108100), the National Natural Science Foundation of China (NO.62006180) and Postgraduate Teaching Reform Project of Yan'an University under Grant YDYJG2019016.

REFERENCES

- G. Castellano, L. Kessous, and G. Caridakis. Emotion recognition through multiple modalities: Face, body gesture, speech. *Springer Berlin Heidelberg*, 2008.
- [2] Dima Damen, Hazel Doughty, Giovanni Maria Farinella, Sanja Fidler, Antonino Furnari, Evangelos Kazakos, Davide Moltisanti, Jonathan Munro, Toby Perrett, Will Price, editor=Ferrari Vittorio Wray, Michael, Martial Hebert, Cristian Sminchisescu, and Yair Weiss. Scaling egocentric vision: The dataset. In European Conference on Computer Vision, 2018.
- [3] Matteo Dunnhofer, Antonino Furnari, Giovanni Maria Farinella, and Christian Micheloni. Visual object tracking in first person vision. *International Journal of Computer Vision*, 131:259 – 283, 2022.
- [4] Basura Fernando and Samitha Herath. Anticipating human actions by correlating past with the future with jaccard similarity measures. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13219– 13228, 2021.
- [5] Antonino Furnari and Giovanni Maria Farinella. What would you expect? anticipating egocentric actions with rolling-unrolling lstms and modality attention. In *International Conference on Computer Vision*, 2019.
- [6] J. Gao, Z. Yang, and R. Nevatia. Red: Reinforced encoder-decoder networks for action anticipation. In *British Machine Vision Conference*, 2017.
- [7] R De Geest and T. Tuytelaars. Modeling temporal structure with lstm for online action detection. In *IEEE Winter Conference on Applications of Computer Vision*, pages 1549–1557, 2018.
- [8] Rohit Girdhar and Kristen Grauman. Anticipative video transformer. *IEEE/CVF International Conference on Computer Vision*, pages 13485–13495, 2021.
- [9] X. Gu, J. Qiu, Y. Guo, B. Lo, and G. Z. Yang. Transaction: Icl-sjtu submission to epic-kitchens action anticipation challenge. 2021.

- [10] Jingjing Jiang, Zhixiong Nan, Hui Chen, Shi tao Chen, and Nanning Zheng. Predicting short-term next-activeobject through visual attention and hand position. *Neurocomputing*, 433:212–222, 2021.
- [11] Yin Li, Miao Liu, and James M. Rehg. In the eye of beholder: Joint learning of gaze and actions in first person video. In *European Conference on Computer Vision*, 2018.
- [12] Tianshan Liu and Kin-Man Lam. A hybrid egocentric activity anticipation framework via memory-augmented recurrent and one-shot representation forecasting. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13894–13903, 2022.
- [13] Zhixiong Nan and Tao Xiang. Third-person view attention prediction in natural scenarios with weak information dependency and human-scene interaction mechanism. *IEEE Transactions on Circuits and Systems for Video Technology.*, 2023.
- [14] Zhixiong Nan, Tianmin Shu, R. Gong, Shu Wang, Ping Wei, Song-Chun Zhu, and Nanning Zheng. Learning to infer human attention in daily activities. *Pattern Recognit.*, 103:107314, 2020.
- [15] Zhixiong Nan, Jingjing Jiang, Xiaofeng Gao, Sanping Zhou, Weiliang Zuo, Ping Wei, and Nanning Zheng. Predicting task-driven attention via integrating bottomup stimulus and top-down guidance. *IEEE Transactions* on *Image Processing*, 30:8293–8305, 2021.
- [16] Zhaobo Qi, Shuhui Wang, Chi Su, Li Su, Qingming Huang, and Qi Tian. Self-regulated learning for egocentric video activity anticipation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021.
- [17] Fadime Sener, Dipika Singhania, and Angela Yao. Temporal aggregate representations for long-range video understanding. In *European Conference on Computer Vision*, pages 154–171. Springer, 2020.
- [18] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need. arXiv, 2017.
- [19] Yu Wu, Linchao Zhu, Xiaohan Wang, Yi Yang, and Fei Wu. Learning to anticipate egocentric actions by imagination. *IEEE Transactions on Image Processing*, 30:1143–1152, 2020.
- [20] Zeyun Zhong, David Schneider, Michael Voit, Rainer Stiefelhagen, and Jürgen Beyerer. Anticipative feature fusion transformer for multi-modal action anticipation. In *IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 6057–6066, 2023.
- [21] Zhen zhong Lan, Lei Bao, Shoou-I Yu, Wei Liu, and Alexander G. Hauptmann. Multimedia classification and event detection using double fusion. *Multimedia Tools and Applications*, 71(1):333–347, 1 2014.