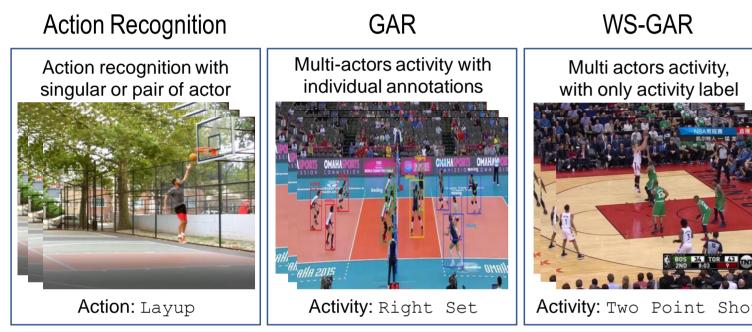
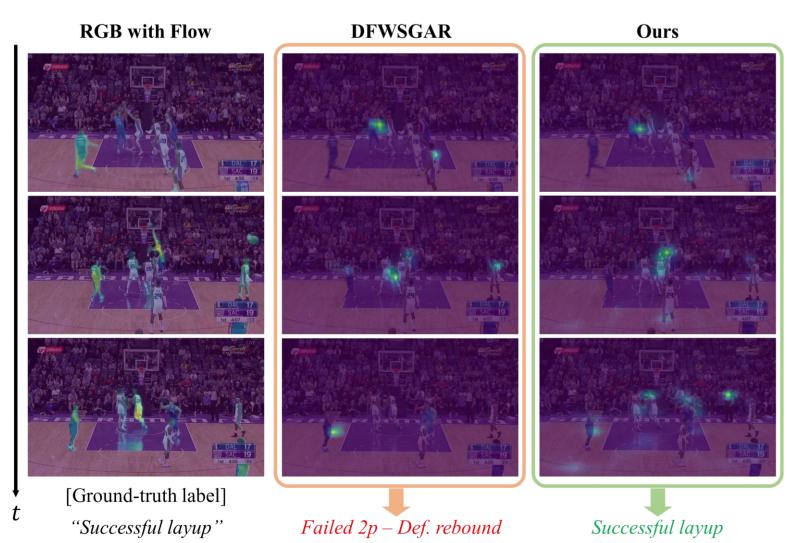


## Introduction

 WSGAR (Weakly Supervised Group Activity) Recognition) requires the model to find actors and their complex spatio-temporal relations with no individual actor annotations provided.



- Flaming-Net selectively highlights key actors, those who play important roles in the activity.
- Utilize optical flow as learning guidance to be more aware of actively moving actors.



# Flow-Assisted Motion Learning Network (Flaming-Net) for Weakly-Supervised Group Activity Recognition M.A. Nugroho, S. Woo, S. Lee, J. Park, Y. Wang, D. Kim, and C. Kim Korea Advanced Institute of Science and Technology

Actor Path

## Method

- Motion-aware actor encoder generates actor features by transforming a set of actor queries into features representing key actors.
- The actor relation module learns relations between actors to infer activity.
- Maintain efficiency by utilizing only the RGB frames in the inference stage.

Temporal

Convolution

Actor

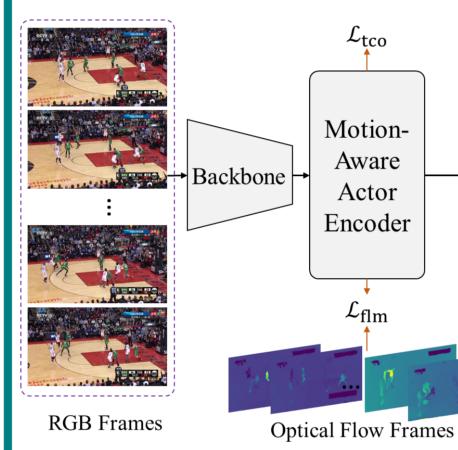
Relation

MHSA

Shared weights

Frame-level

classifier



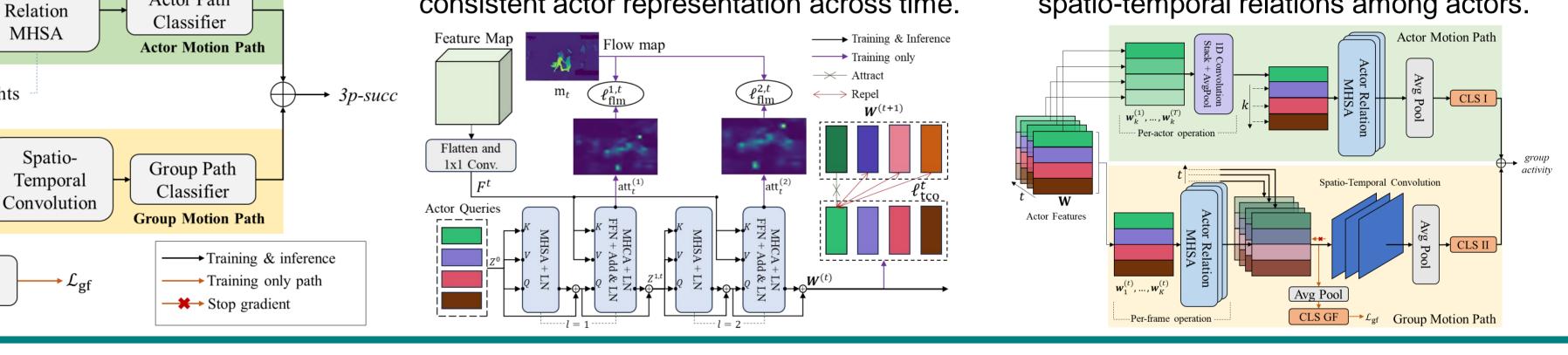
## Results





In failed 2p - def. reb., Flaming-Net highlights the scrimmage and the rebound action

- The encoder consists of multi-head attention modules with learnable actor queries.
- The attentions are guided by the optical flow The actor motion path focuses on the temporal evolution of individual actors. using aux. loss  $\mathcal{L}_{flm}$  to highlight active actors. The group motion path focuses on local
- Temporal contrastive loss helps to create spatio-temporal relations among actors. consistent actor representation across time.



#### High attention to important players on crucial moments

In 3p-success, Flaming-Net first highlights the shooter, then the def. players and referee

Actor

## Performance in NBA

spatial and long temporal actor relationships.								$\mathcal{L}_{tco}$	$\mathcal{L}_{ ext{flm}}$	MC	AI	MPCA
Method	Pub.	F	#Params	FLOPs	MCA	MPCA	L <sub>gf</sub> ×	×	×	75.3	%	70.1%
SAM	ECCV'20	×	25.5M	304 G	44.2%	59.3%	$\checkmark$	×	×	78.3	%	72.3%
Dual-AI	CVPR'22	$\checkmark$	-	_	58.1%	50.2%	$\checkmark$	$\checkmark$	×	77.5	%	73.0%
DFWSGAR	CVPR'22	x	17.5M	313G	75.8%	71.2%	$\checkmark$	×	$\checkmark$	77.5	%	73.0%
LRMM+GCM	ImaVis'23	x	14.2M	306G	77.8%	73.2%	$\checkmark$	$\checkmark$	$\checkmark$	79.1	%	76.0%
Flaming-Net	ECCV'24	Tr	13.8M	307G	79.1%	76.0%	Effect of actor relation module					
Performance in WS-Volleyball dataset.							Actor Relation MCA N					MPCA
Method	Pub.	F	Backbone		MCA	MPCA	Actor Motion Path (AMP)			74.3%	73.9%	
SAM	ECCV'20	x	ResNet-18		86.3%	93.1%	AMP + Losses			77.1%	71.7%	
Dual-AI	CVPR'22	$\checkmark$	Inception-v3		-	96.5%	S.T Transformer Dual Path			77.0%	70.7%	
DFWSGAR	CVPR'22	×	ResNet-18		90.5%	94.4%	Flaming-Net			79.1%	76.0%	
LRMM+GCM	ImaVis'23	×	ResNet-18		92.8%	95.6%	Мс	More results and analysis on our pap				
Flaming-Net	ECCV'24	Tr	Inception-v3		93.3%	95.2%		Visit our lab at: <i>cilabs.kaist.ac.k</i>				
F = Optical Flow, Tr = Use	optical flow only i	n training					VISIL			203.1	<u>naisi.c</u>	<u>au.ni</u>



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The actor relation module consists of

actor motion and group motion path.

### dataset containing complex

#### Efficacy of auxiliary losses