



# **EMAG: Ego-motion Aware and Generalizable 2D Hand Forecasting from Egocentric Videos**

Masashi Hatano<sup>1</sup> Ryo Hachiuma<sup>2</sup> Hideo Saito<sup>1</sup> <sup>1</sup>Keio University <sup>2</sup>NVIDIA



EUROPEAN CONFERENCE ON COMPUTER VISION

## **Overview**

First work that investigates the potential benefits of incorporating ego-motion in egocentric 2D hand forecasting task > Propose simple but effective approach, EMAG Validated on Ego4D and EPIC-Kitchens in intra and cross-dataset scenarios

## **Proposed Method**



## Background



<ul> <li>Object 1 token</li> <li>Object 2 token</li> <li>RGB token</li> <li>Ego-motion token</li> <li>Ego learnable token</li> </ul>	<ul> <li>Left hand token</li> <li>Right hand token</li> <li>Flow token</li> <li>Hand learnable token</li> </ul>

## **Experimental Results**

#### Intra & Cross-Dataset Evaluation

Method	Ego4D -	$\rightarrow \text{Ego4D}$	EPIC -	$\rightarrow \text{EPIC}$	EPIC $-$	→ Ego4D	Ego4D	$\rightarrow \text{EPIC}$
	ADE $\downarrow$	FDE $\downarrow$	ADE $\downarrow$	FDE $\downarrow$	$ ADE\downarrow $	FDE $\downarrow$	ADE $\downarrow$	FDE $\downarrow$
CVM [1]	108.11	143.23	141.70	155.40	108.11	143.23	141.70	155.40
$\mathrm{KF}\left[2\right]$	71.23	72.87	70.58	75.60	71.23	72.87	70.58	75.60
Seq2Seq[3]	55.91	60.72	62.24	67.85	62.43	67.85	67.97	72.26
OCT [4]	49.40	54.73	53.85	59.06	57.74	59.10	64.97	65.84
I3D + Regression [5]	49.27	<u>53.04</u>	49.64	54.83	59.72	61.72	51.70	<u>58.37</u>
Ours	<b>48.99</b>	52.83	<b>48.78</b>	54.03	53.67	56.36	51.03	56.78

#### Issues

#### **1. Ego-motion incorporation**

- Take ego-motion as input ullet
- Forecasting future ego-motion  $\bullet$

#### **2.** Generalization ability

Robustness to novel scene

### **Task Definition**

**Task: 2D Hand Forecasting** Observation: 2s, Forecsting: 1s

 $x_{p1}$ : frame 0.25s after the last observed frame  $x_{p2}$ : frame of 0.5s after  $x_{p3}$ : frame of 0.75s after  $x_{p4}$ : frame of 1s after

Predict hand location  $(\widehat{h}_{i}^{l}, \widehat{h}_{i}^{r})$ , where  $i \in \{p1, p2, p3, p4\}$ , on 2D image coordinate

## Limitations & Future Work

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## **Qualitative Results**

Object D	DOD		<b>D</b>	Int	Ira	Cross		
UDJECT KGB Flow Ege		Ego	$ADE \downarrow$	$FDE \downarrow$	ADE $\downarrow$	$FDE \downarrow$		
	$\checkmark$	$\checkmark$	$\checkmark$	48.76	53.79	52.78	57.02	
$\checkmark$		$\checkmark$	$\checkmark$	50.08	54.83	53.30	57.54	
$\checkmark$	$\checkmark$		$\checkmark$	51.00	54.78	$54,\!74$	57.93	
$\checkmark$	$\checkmark$	$\checkmark$		<b>48.35</b>	<b>53.24</b>	52.89	57.02	
$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	48.89	53.43	52.35	56.57	

**Input Ablation** 

Method	Int	tra	$\operatorname{Cross}$		
	$\overline{ADE}\downarrow$	FDE $\downarrow$	ADE $\downarrow$	FDE ↓	
$ m w/o~\mathcal{L}_{ego}$	49.66	54.26	52.84	57.08	
${ m w}/~{\cal L}_{ m ego}~({ m Ours})$	48.89	<b>53.43</b>	52.35	56.57	

- Forecasting in 3D
- More interesting scenario where hands are out-of-view in several frames during observation

• GT

• Ours

#### References

- [1] Schöller et al, What the constant velocity model can teach us about pedestrian motion prediction, RA-L (2020)
- [2] Kalman et al, A new approach to linear filtering and prediction problems, Journal of Basic Engineering (1960)
- [3] Sutskever et al, Sequence to sequence learning with neural networks, NeurIPS (2014)
- [4] Liu et al, Joint Hand Motion and Interaction Hotspots Prediction from Egocentric Videos, CVPR(2022)
- [5] Grauman et al, Ego4D: Around the World in 3,000 Hours of Egocentric Video, CVPR(2022)
- Ego4I



OCT

• **I3D**