In the Eye of Transformer: Global-Local Correlation for Egocentric Gaze Estimation

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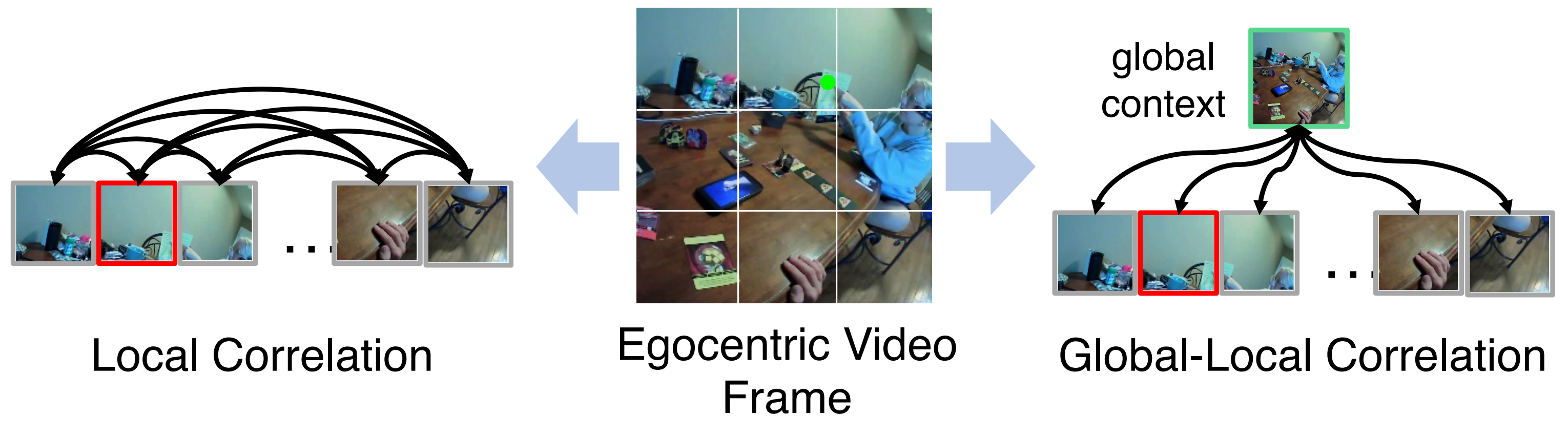
Motivation

- Egocentric gaze implies human's attention in daily activities, which is critical for applications in AR/VR.
- There are too many items disturbing our prediction in a complicated scene.
- Global-local correlation is not well captured in self-attention mechanism.

How do you know where I am looking at?



Gaze estimation in a holistic view:

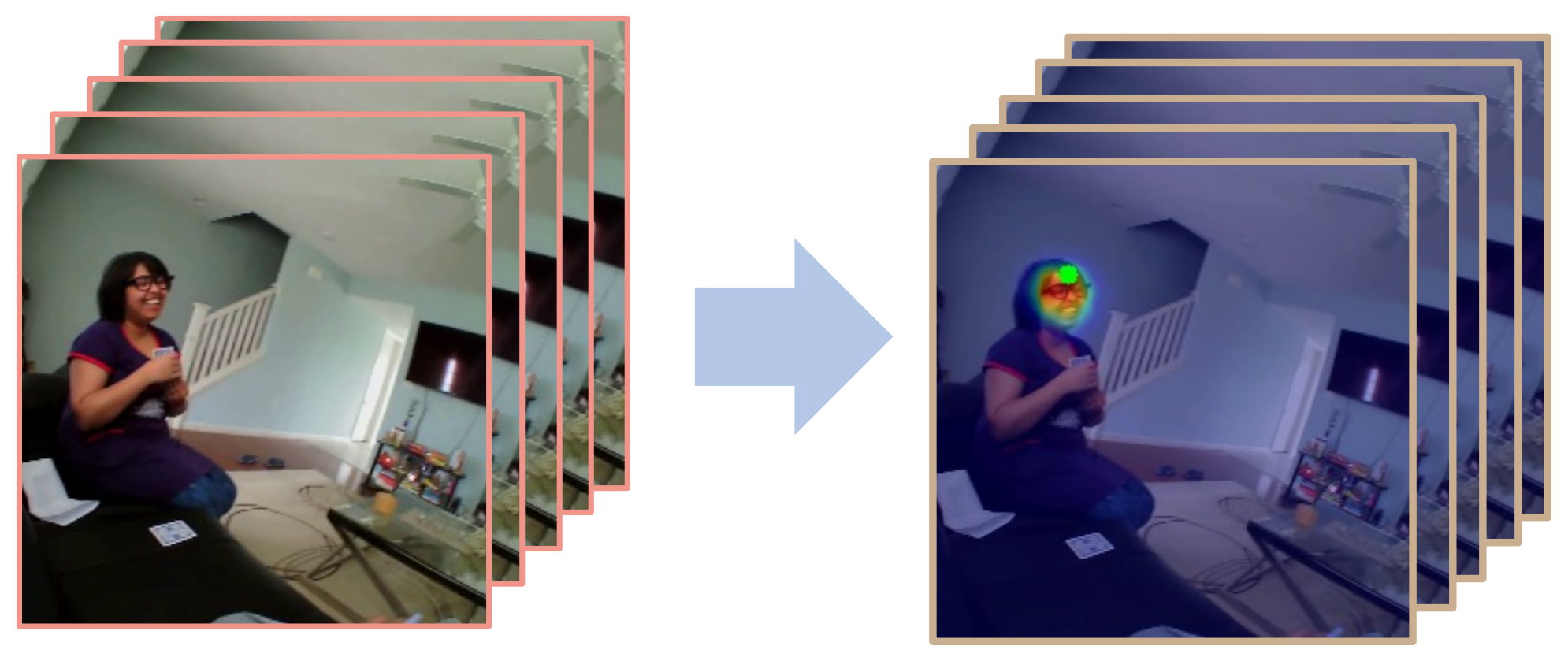
Another person is pointing at and looking at the sheet she holds.

Correlations across only local visual tokens are insufficient to distinguish gaze fixation in complex background!

Objective

Input: egocentric video sequence

Output: gaze prediction in each frame (heatmap)



Gaze labels are captured by eye trackers.

Challenge:

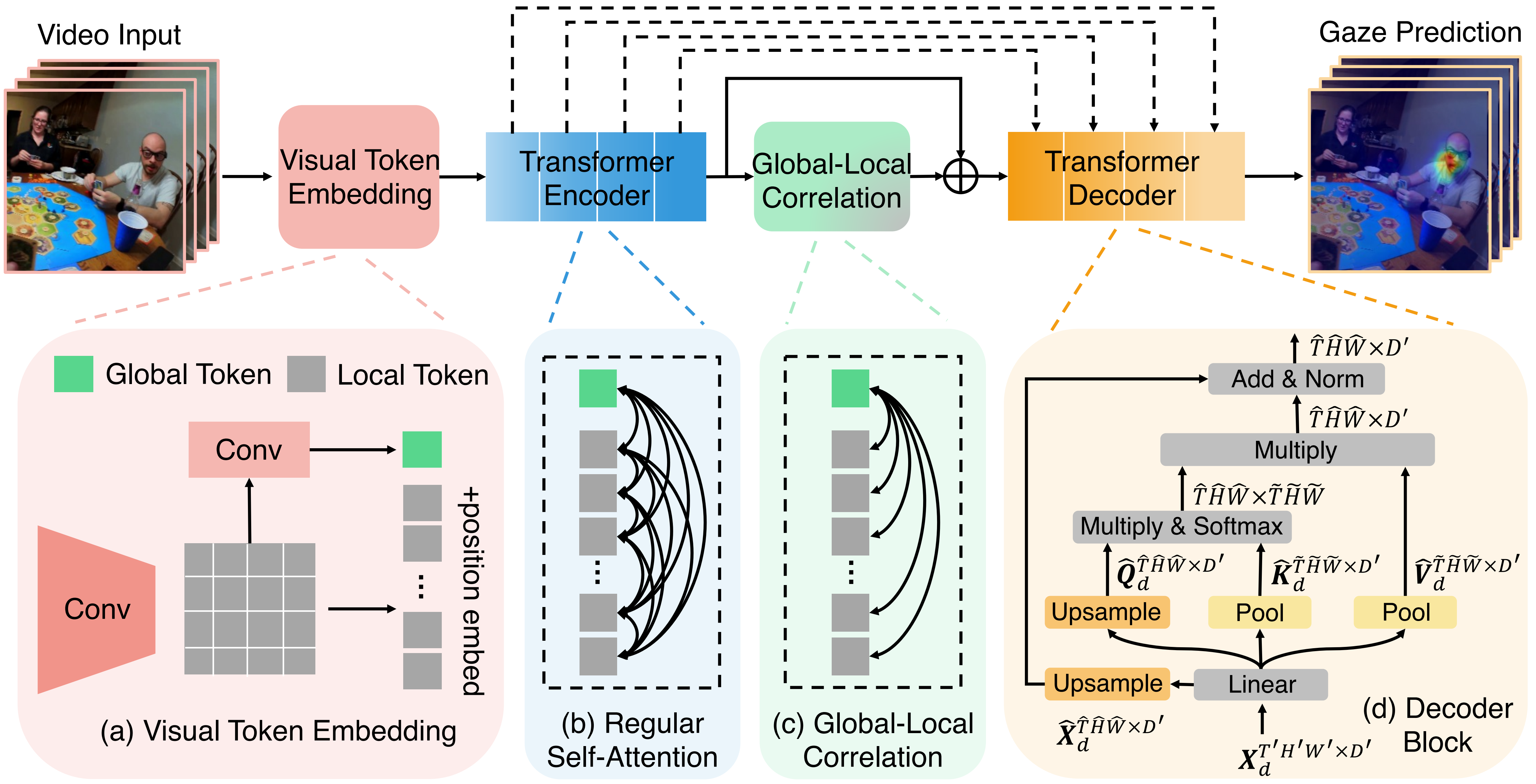
- Gaze can move fast and background changes drastically.
- We need to integrate cues from a global view into a holistic analysis of visual attention.

Key Idea:

- Encoding the global context into an additional token.
- Highlighting the correlation of global token and each local token in a specifically designed module.

Contact:

Overview of Architecture


Video Input
Visual Token Embedding
Transformer Encoder
Global-Local Correlation
Transformer Decoder
Gaze Prediction
Global Token
Local Token
Conv
Conv
+position embed
(a) Visual Token Embedding
(b) Regular Self-Attention
(c) Global-Local Correlation
$\hat{T}\hat{H}\hat{W}\times D'$
Add & Norm
$\hat{T}\hat{H}\hat{W}\times D'$
Multiply
$\hat{T}\hat{H}\hat{W}\times\tilde{T}\tilde{H}\tilde{W}$
Multiply & Softmax
$\hat{Q}_d^{\hat{T}\hat{H}\hat{W}\times D'}$
$\hat{K}_d^{\tilde{T}\tilde{H}\tilde{W}\times D'}$
$\hat{V}_d^{\tilde{T}\tilde{H}\tilde{W}\times D'}$
Upsample
Pool
Pool
Upsample
Linear
$\hat{X}_d^{\hat{T}\hat{H}\hat{W}\times D'}$
$X_d^{T'H'W'\times D'}$
(d) Decoder Block

Regular Self-Attention vs. Global-Local Correlation

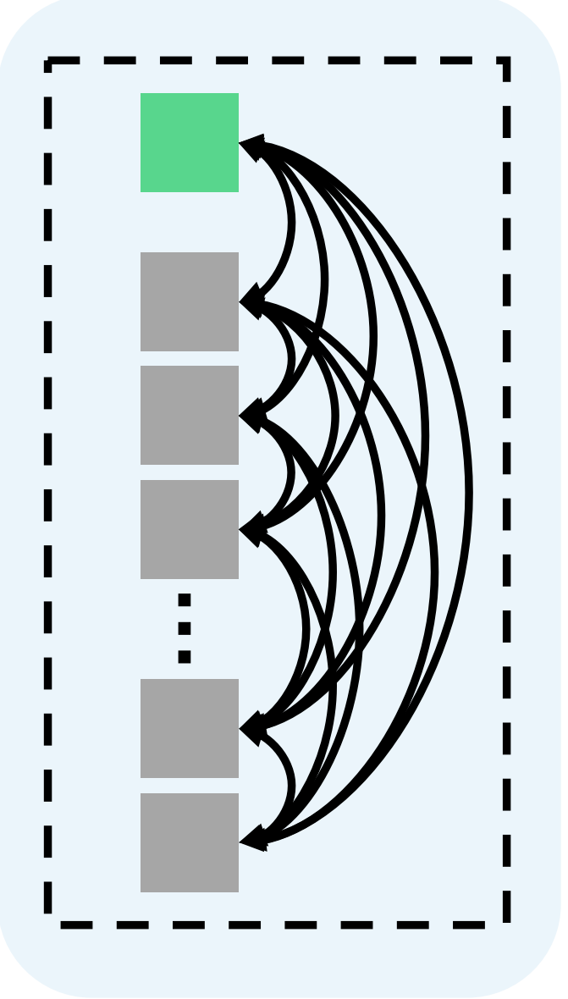
Input: $X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_{N+1} \end{bmatrix} \in \mathbb{R}^{(N+1)\times D}$

global token

local tokens

$$[\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}] = Linear(\boldsymbol{X}) \quad (\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V} \in \mathbb{R}^{(N+1)\times D})$$

Linearly map each token x_i to query, key and value vectors.



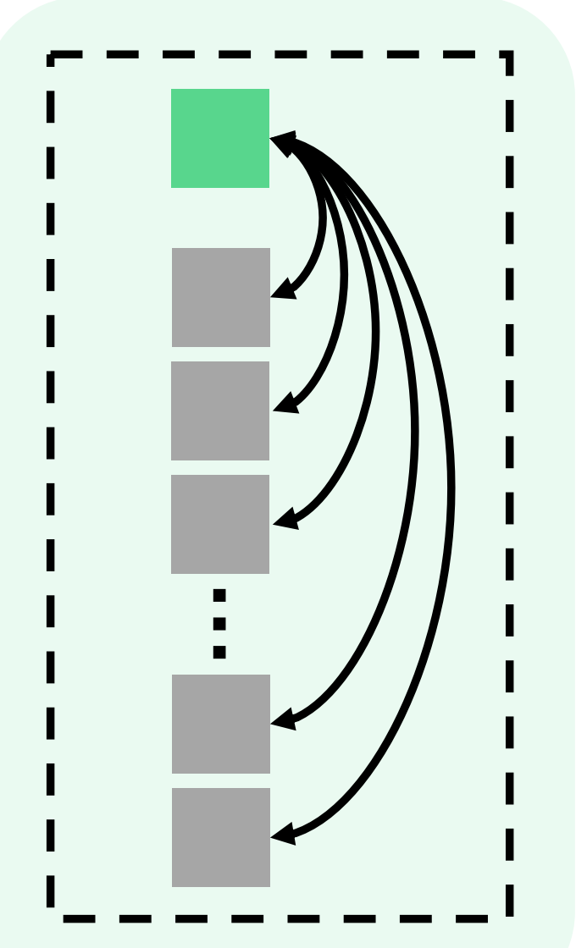
Regular Self-attention:

$$Attention(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = Softmax\left(\boldsymbol{Q}\boldsymbol{K}^T/\sqrt{D}\right)\boldsymbol{V} \in \mathbb{R}^{(N+1)\times D}$$

Global-Local Correlation:

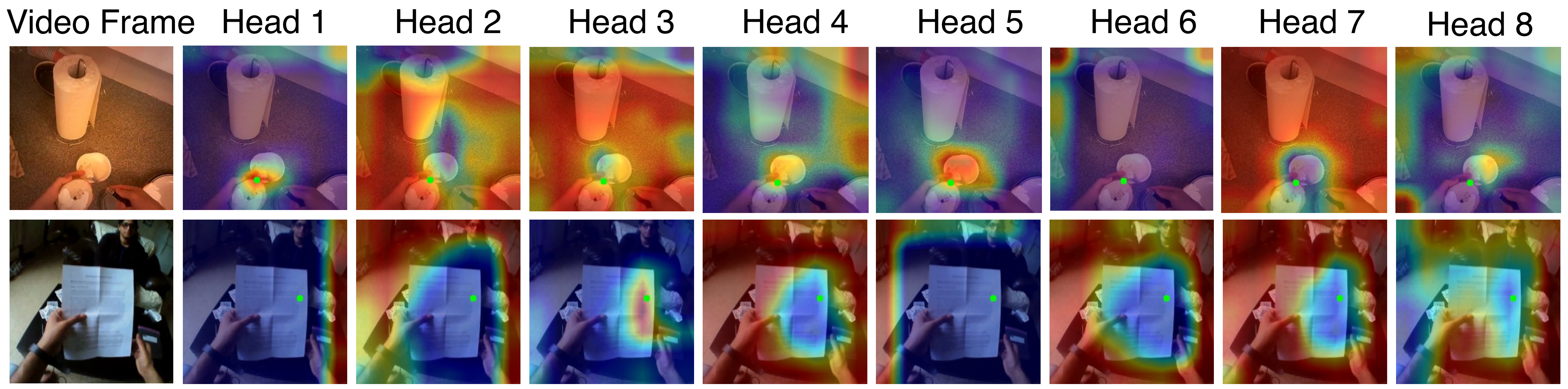
$$\boldsymbol{S}^{(N+1)\times(N+1)} = [s_{i,j}] \quad s_{i,j} = \begin{cases} 0, & if\ i=j\ or\ j=1 \\ 10^8, & otherwise \end{cases}$$

$$GLC(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = Softmax\left((\boldsymbol{Q}\boldsymbol{K}^T-\boldsymbol{S})/\sqrt{D}\right)\boldsymbol{V}$$

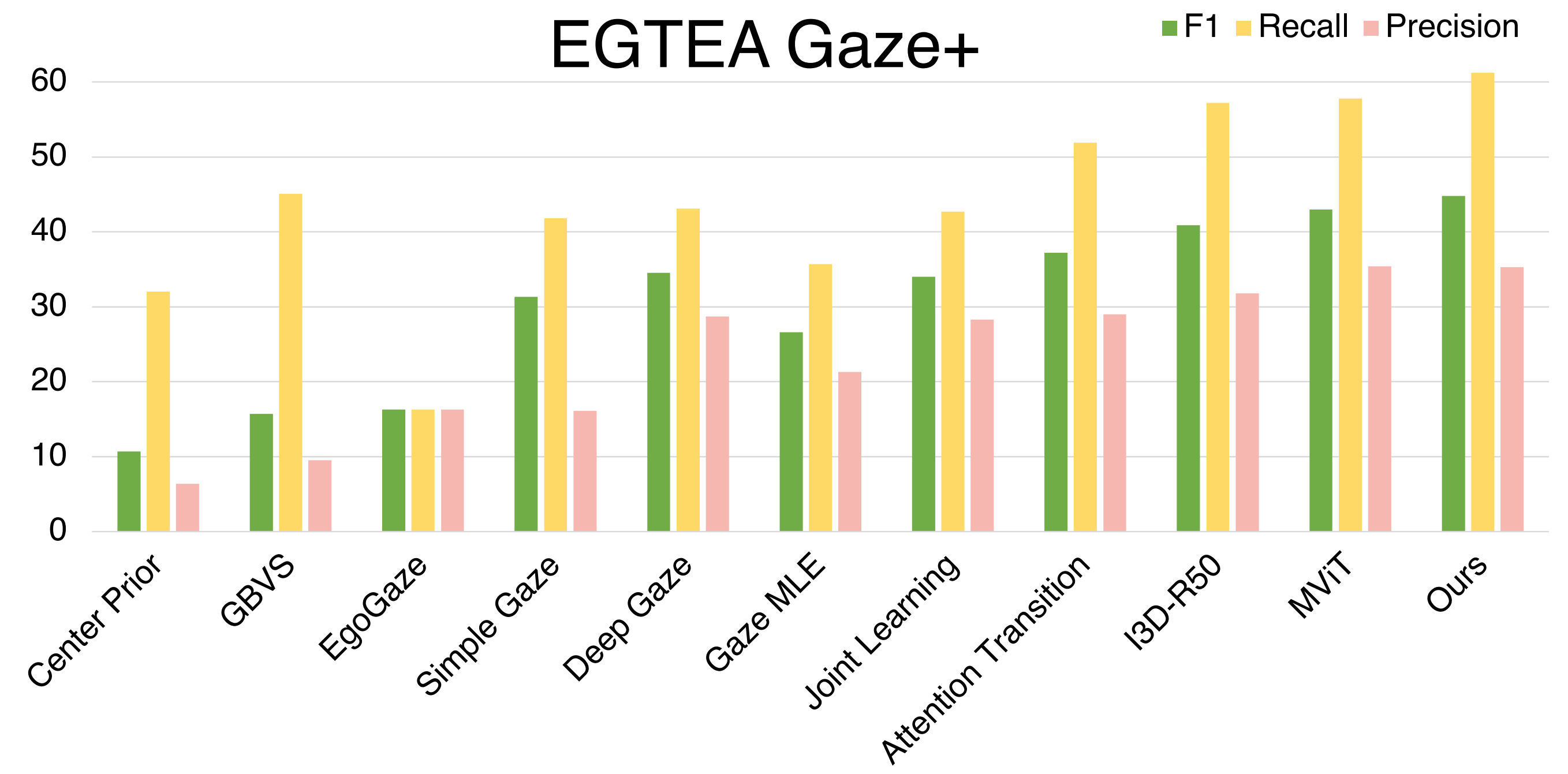


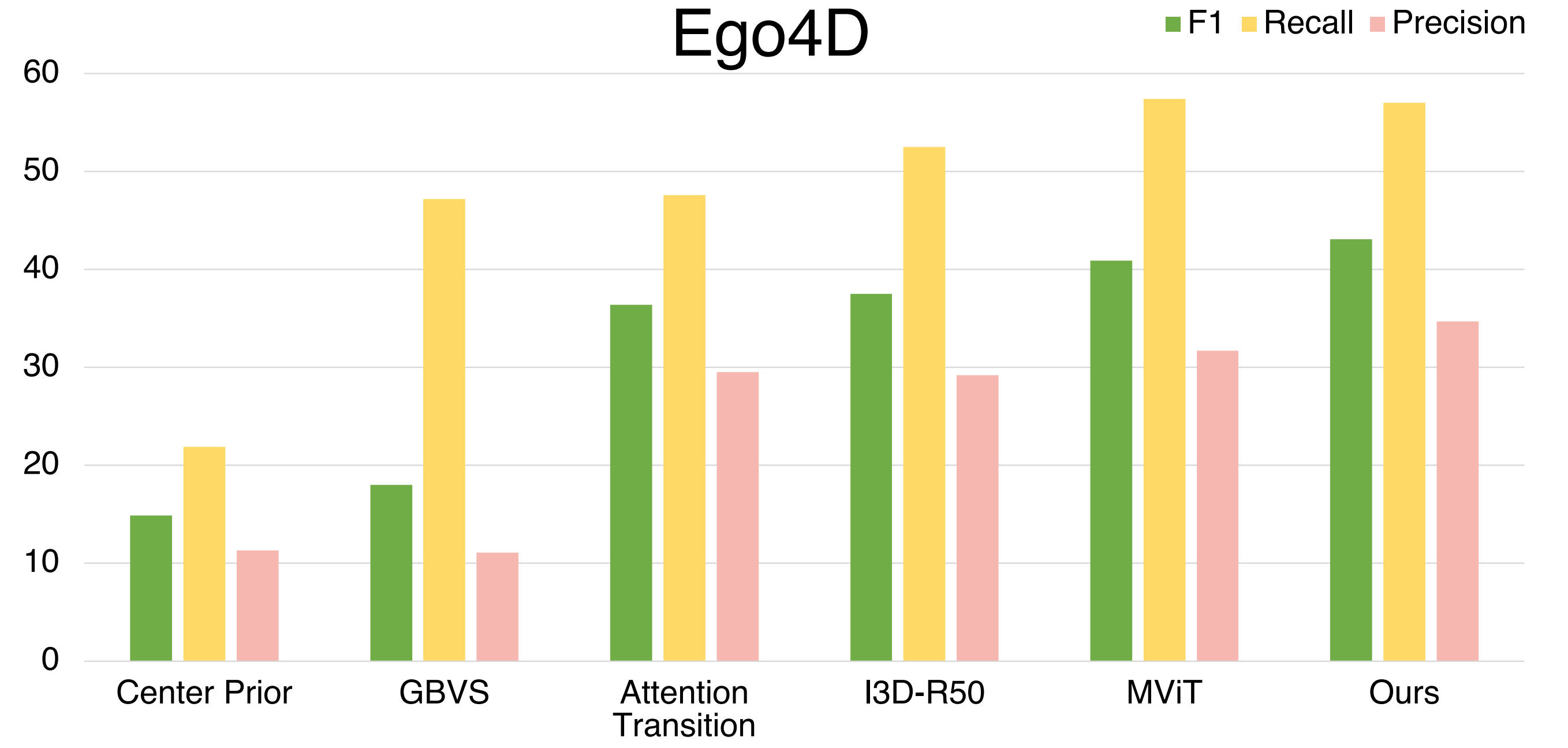
Key point: Correlations across local tokens are ignored by subtracting a suppression matrix.

Visualization of Attention in GLC

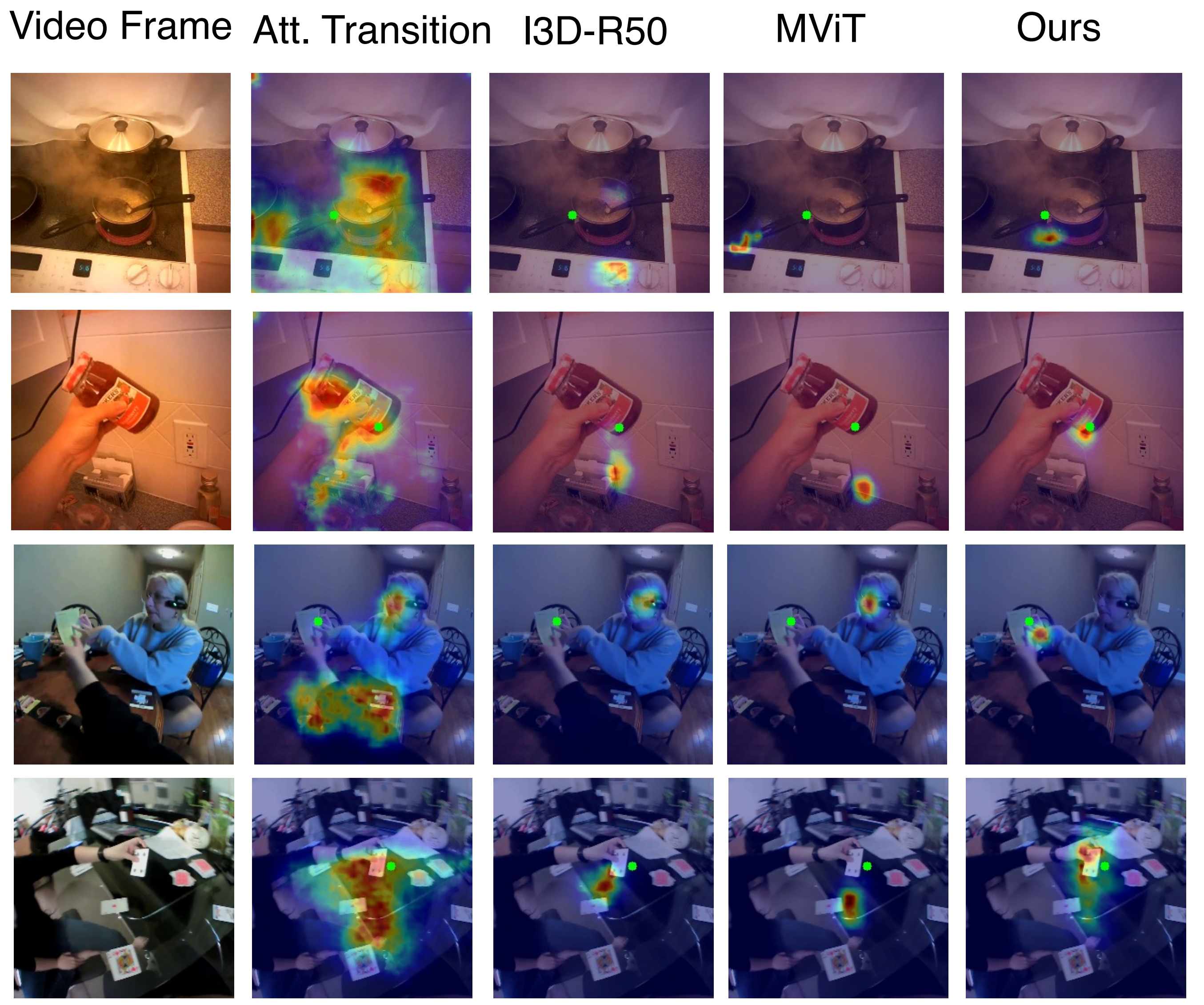


Experiments and Results





Visualization of Prediction



Conclusion

We develop the first transformer-based model for gaze estimation on egocentric videos. Our proposed method facilitates strong gaze representation learning and achieves new state of the art.

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