Aligning Neuronal Coding of Dynamic Visual Scenes with Foundation Vision Models (Supplementary Materials)

Rining Wu[1,2], Feixiang Zhou[3], Ziwei Yin[2], and Jian K. Liu[1,2]

[1] University of Leeds ml20r2w@leeds.ac.uk
[2] University of Birmingham {z.yin.3, j.liu.22}@bham.ac.uk
[3] Lancaster University f.zhou3@lancaster.ac.uk

1 SD-KL Metric

For considering the duration of spikes, we designed a metric called Spike Duration — Kullback-Leibler Divergence (SD-KL). The pseudocode of SD-KL is demonstrated in Algorithm 1.

Algorithm 1 Pseudocode of the SD-KL

Input: $\hat{y} \in \mathbb{R}^{N \times F}, y \in \mathbb{R}^{N \times F}, \alpha = 0.3, \beta = 1.0$
Output: score

$\hat{\mathcal{D}} \leftarrow$ **peak widths**$(\min(\max(0, \hat{y}), \beta)), \hat{\mathcal{D}} \subset \mathbb{R}$
$\mathcal{D} \leftarrow$ **peak widths**$(\min(\max(0, y), \beta)), \mathcal{D} \subset \mathbb{R}$
$Var_{\cup} \leftarrow \frac{\alpha}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2, x_i \in \{D, \hat{D}\}$
$\mathcal{L}_{\cup} \leftarrow \left\{ (lower_{\cup} - 3 * Var_{\cup}) + i \cdot \frac{(upper_{\cup} + 3 * Var_{\cup}) - (lower_{\cup} - 3 * Var_{\cup})}{199} \mid i = 0, 1, \ldots, 199 \right\}$
$pdf_{\mathcal{D}} \leftarrow$ **KDE**$(\mathcal{D}, \alpha)$
$pdf_{\hat{\mathcal{D}}} \leftarrow$ **KDE**$(\hat{\mathcal{D}}, \alpha)$
$P_{\mathcal{D}} = \left\{ \left(x_i, \frac{pdf_{\mathcal{D}}(x_i)}{\sum_{j=1}^{N} pdf_{\mathcal{D}}(x_j)} \right) \mid x_i \in \mathcal{L}_{\cup} \right\}$
$P_{\hat{\mathcal{D}}} = \left\{ \left(x_i, \frac{pdf_{\hat{\mathcal{D}}}(x_i)}{\sum_{j=1}^{N} pdf_{\hat{\mathcal{D}}}(x_j)} \right) \mid x_i \in \mathcal{L}_{\cup} \right\}$
score $\leftarrow D_{KL}(P_{\hat{\mathcal{D}}} || P_{\mathcal{D}})$
score $\leftarrow \min(\max(0, \text{score}), 1000)$
return score

Where α is the bandwidth of the kernel density estimation (KDE), set to 0.3, β is the high cut of the spike duration, set to 1.0, N is the number of RGCs, F is the number of frames, and $y, \hat{y}$ are the ground truth and predicted FR, respectively. Furthermore, the *peak widths* calculates durations of each spike then returns the set of durations [1]. The KDE algorithm calculates the probability density function (PDF) of the input set of durations with a given bandwidth α.

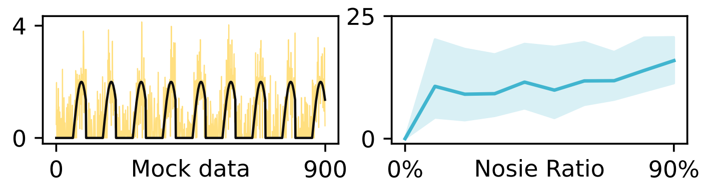
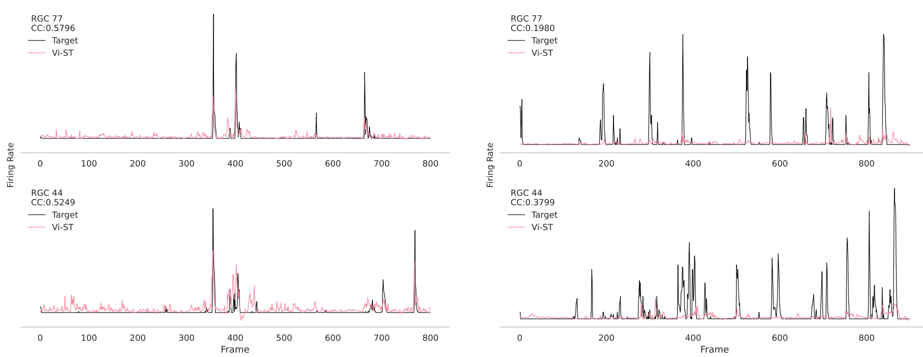


Fig. 1: SD-KL Metric Baseline

We selected several signals simulated using *the sine function* and added random noise at different ratios to obtain the baseline of the SD-KL metric, as Fig. 1.

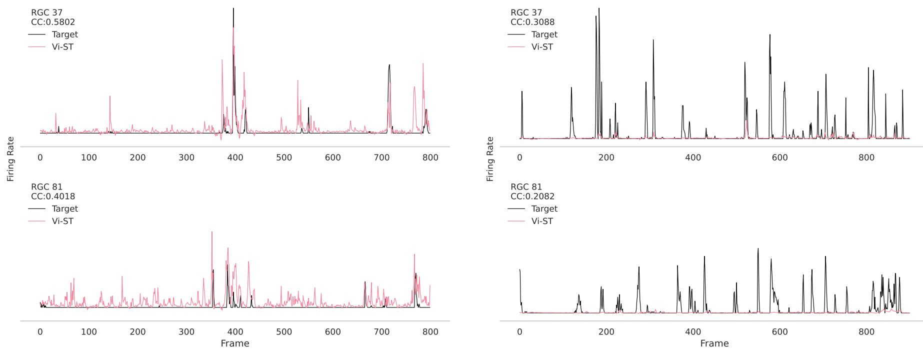
2 Experimental Results

We choose the best, middle, and worst cases of the CC to demonstrate the real predictions of the Vi-ST.



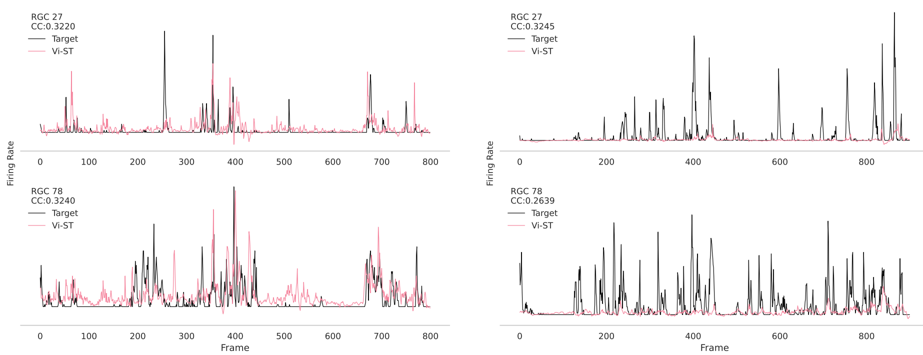
(a) *Mov1→Mov2* **(b)** *Mov2→Mov1*

Fig. 2: Real Predictions of good CC



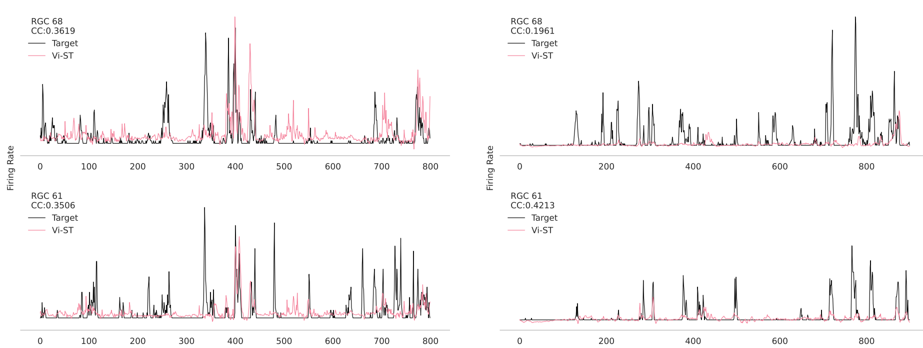
(a) *Mov1→Mov2* **(b)** *Mov2→Mov1*

Fig. 3: Real Predictions of good CC



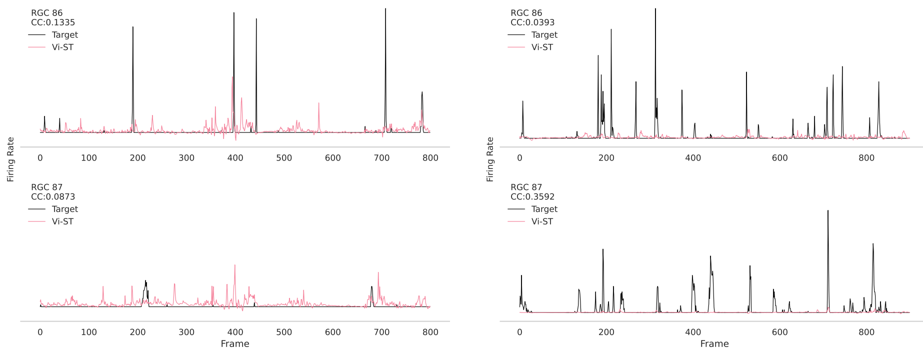
(a) *Mov1→Mov2* **(b)** *Mov2→Mov1*

Fig. 4: Real Predictions of middle CC



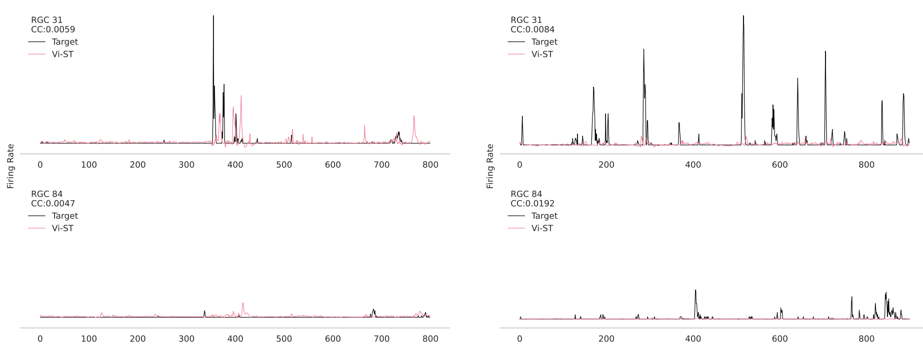
(a) *Mov1→Mov2* **(b)** *Mov2→Mov1*

Fig. 5: Real Predictions of middle CC



(a) *Mov1→Mov2* **(b)** *Mov2→Mov1*

Fig. 6: Real Predictions of worst CC



(a) *Mov1→Mov2* **(b)** *Mov2→Mov1*

Fig. 7: Real Predictions of worst CC

References

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