A Extended Architecture Overview

The Spiking Transformer layer primarily consists of a spiking multi-head attention (MHA) block, followed by a spiking feedforward network comprising an intermediate layer and an output layer with both inter- and intra-layer communication happening using spikes. Details of the operations in each layer are provided below.

Spiking Attention Block: In Spiking MHA, to enable computationally efficient accumulate based operations the input to the attention layer are spikes instead of real-valued data. The spiking attention mechanism [26] is given as follows,

$$Attn(X_s[t], K_s[t], V_s[t]) = \phi(d * Q(X_s[t]) \cdot (K_s[t])^T) \cdot V_s(t) \tag{8}$$

Here, $Q(X_s(t))$ represents the Query, obtained by passing the input spikes $X_s(t)$ at time t through a linear layer (W_Q). The spikes for the Key layer ($K_s(t)$) are generated by passing $X_s(t)$ through a linear mapping (W_K), followed by an LIF neuron layer. Similarly, we generate spikes for Value. d is a scaling constant. Since the input, key, and value matrices consist of spike trains rather than real-valued data, the primary computations in all matrix multiplications are floating-point accumulation operations rather than floating point multiplicative and accumulative operations. In the (NF)-SpikingVTG variant, as discussed in the paper, we use ϕ as the $ReLU$ and scaling operation, significantly reducing the computational overhead compared to employing ϕ as the non-local $Softmax$ operation. The output of the attention layer is fed to an LIF neuron, which outputs spikes. The convergence dynamics of the layer at equilibrium is given as, $a^*_{attn} = \sigma(\frac{1}{V_{th}}(Attn(a^*_x, a^*_k, a^*_v) + b_{attn})$, where a_x represents the ASR of the layer used to generate the Query, a_k denotes the ASR of the Key, and a^*_v corresponds to the ASR of the Value. b_{attn} is a bias term.

Intermediate Layer: The intermediate layer takes as input the spikes generated from the preceding layer and maps it to an intermediate dimension with a linear layer. The output is then passed through an LIF layer. The convergence dynamics of the layer at equilibrium is given as, $a^*_{interm.} = \sigma(\frac{1}{V_{th}}(act(W_{interm.}a^*_p)+b_{interm.}))$, where $W_{interm.}$ is the linear weight and gelu() is the activation used for the layer. a^*_p is the ASR at equilibrium for the previous layer. $b_{interm.}$ is a bias term. In this paper, we have used explored different choices for act, such as $GELU$ and $ReLU$. During inference, all matrix multiplications involve accumulative operations due to the nature of the input.

Output Layer: The output layer takes as input the spikes generated from the preceding layers as shown in Fig. 1. The output is then passed through an LIF layer. The convergence dynamics of the layer at equilibrium is given as, $a^*_{output} = \sigma(\frac{1}{V_{th}}(norm(W_{output}a^*_{interm.} + a^*_p) + b_{output}))$, where W_{output} is the linear weight and layer norm is used for normalization. $a^*_{interm.}$ is the ASR at equilibrium for the previous intermediate layer. b_{output} is a bias term. During inference, all matrix multiplications involve accumulative operations due to the nature of the input. In the (NF)-SpikingVTG model we further remove the layer normalization to improve on-chip deployability.

B Loss Function Details

As described in the main paper, the total loss over N clips in the training set is defined as $L = \frac{1}{N}\sum_{i=1}^{N}(L_{f_i} + L_{d_i} + L_{c_i})$, where L_f represents the binary cross-entropy loss for the indicator variable f_i, L_d combines the smooth L1 loss with the generalized IoU loss [31] for the predicted boundaries, and L_c is an optional loss term incorporating intra- and inter-video contrastive learning [32]. We follow similar loss function construction as previous works on VTG [1, 6]. The loss for fore-ground parameter is given as follows,

$$L_f = -\lambda_f \left[f_i \log \tilde{f}_i + (1 - f_i) \log(1 - \tilde{f}_i) \right] \tag{9}$$

where, f_i is the true label and $\tilde{f}_i$ is the model prediction. The loss for predicted boundaries is given as follows,

$$L_d = \mathbf{1}_{f_i=1} \left(\lambda_{\text{L1}} L_{\text{SmoothL1}}(\tilde{d}_i, d_i) + \lambda_{\text{iou}} L_{\text{iou}}(\tilde{b}_i, b_i) \right) \tag{10}$$

where, d_i, b_i are the true label and $\tilde{d}_i, \tilde{b}_i$ is the model prediction. $L_c = \lambda_{\text{inter}} L_{\text{inter}} + \lambda_{\text{intra}} L_{\text{intra}}$ is used for inter-video and intra video contranstive learning [6]. For each video V, we randomly select a clip v_i with fore-ground indicator = 1 and positive saliency score. Clips from the same video, denoted as v_j, with saliency scores $s_j < s_i$ are treated as negative samples. i.e., $A = \{j \mid s_j < s_i, 1 \leq j \leq L_v\}$, and perform intra-video contrastive learning using the loss

$$L_{\text{intra}} = -\log \frac{\exp(\tilde{s}_i/\tau)}{\exp(\tilde{s}_i/\tau) + \sum_{j \in A} \exp(\tilde{s}_j/\tau)} \tag{11}$$

. Furthermore, we treat textual queries from other samples within the batch ($k \in S$) as negative samples, enabling inter-video contrastive learning for cross-sample supervision:

$$L_{\text{inter}} = -\log \frac{\exp(\tilde{s}_i/\tau)}{\sum_{k \in S} \exp(\tilde{s}_i^k/\tau)} \tag{12}$$

, where S is the training batch, $\tilde{s}_i^k = \cos(v_i, M_k)$ and M_k is the sentence representation (Eqn. 2) and cos is cosine similarity.

C Dataset Details

QVHighlights: The QVHighlights dataset [1] stands out as the sole dataset providing annotations for both moment retrieval and highlight detection, making it an excellent resource for benchmarking on both the VTG tasks. Comprising 10,148 videos with an average duration of 150 seconds. It features a total of 10,310 queries linked to 18,367 moments, resulting in an average of 1.8 distinct moments per query within each video. The dataset spans a variety of scenarios, including daily vlogs, travel vlogs, and news events.

Charades-STA: The Charades-STA [42] dataset comprises 16,128 indoor videos, each with an average duration of 30.6 seconds. It includes 12,408 query-interval pairs designated for training and 3,720 query-interval pairs reserved for testing.

TACoS: TACoS [43] consists of 127 videos, each averaging 4.78 minutes in length. The dataset is split into 75 videos for training, 27 for validation, and 25 for testing.

Youtube Highlights: YouTube Highlights [44] consists of 433 videos across 6 domains, using the domain names as text queries.

D Evaluation Metrics:

For QVHighlights, following previous work [1] we use Recall@1 with IoU thresholds of 0.3, 0.5 and 0.7 and avg. mean average precision (mAP), mAP@0.5 and mAP@0.75 as the evaluation metric for moment retrieval tasks. For highlight detection, we use mAP and HIT@1 [1], where a clip is considered a true positive if it receives a score of "Very Good" [5]. For Charades-STA and TACoS, we employ Recall@1 with IoU thresholds of 0.3, 0.5, and 0.7, along with the mean IoU (mIoU). For Youtube Highlights we use mAP.

E Additional Experimental Details

In this subsection, we provide a concise overview of the implementation details and provide additional experimental details. The GPU specifications for the experiments are detailed in the main paper, while the CPU utilized is an AMD Ryzen Threadripper 3960X 24-Core Processor. We have used Python and the PyTorch framework to write the code. The video and textual feature are developed following previous work [1, 6]. We have used the Adam optimizer to train our model. We list the hyper-parameters used in the work in Table 6. We used grid search to find optimal values.

E.1 Training Stages

Training a multi-modal spiking architecture like SpikingVTG is resource-intensive. To enhance the efficiency of this process and develop computationally efficient variants of our model, we leverage a

Hyper-parameters	Range	Optimal
N: Encoder Layers	(2-6)	4
D: Hidden Dimension	(768-2048)	1024
n_1: f-decoder depth	(1-5)	3
k_1: f-decoder kernel size	(3-9)	3
n_2: d-decoder depth	(1-5)	3
k_2: d-decoder kernel size	(3-9)	7
T_{CLRM}: Timesteps for CLRM	(5-100)	50
T_f: Timesteps for Finetuning	(5-50)	16
V_{th}: Threshold Potential	(0.5 - 2.0)	1.0
γ: Leaky-factor	(0.9 - 1.0)	0.99
λ_f :L$_f$ co-efficient	(1 - 20)	10
λ_{L1} :L$_{SmoothL1}$ co-efficient	(1 - 20)	10
λ_{intra} :L$_{intra}$ co-efficient	(0 - 1.0)	0.05
λ_{inter} :L$_{inter}$-co-efficient	(0 - 1.0)	0.01
λ_{iou} :L$_{iou}$ co-efficient	(1 - 20)	10
λ_{cos}: Sq. cosine weight (CLRM)	(0 - 1.0)	0.2
λ_{l_2}: L_2 weight (CLRM)	(0 - 1.0)	0.8
lr: Learning Rate	(1e$^{-5} - 1e^{-6}$)	8e^{-6}
w_d: weight decay	(1e$^{-5} - 1e^{-3}$)	1e^{-4}
Batch Size	(8-64)	32
Epochs: CLRM	10-100	50
Epochs: Finetuning	20-200	100

Table 6: Hyper-parameters of our SpikingVTG model. Optimal values for QVHighlights dataset is also shown.

multi-staged training framework. We utilize a transformer-based non-spiking VTG model (such as UniVTG) to perform CLRM loss optimization. After this initial stage, we fine-tune SpikingVTG using the true labels. Once the base SpikingVTG model is established, we modify its architecture to remove non-local operations and perform extreme quantization, followed by additional fine-tuning to create computationally efficient variants with minimal performance degradation. The resulting computationally efficient, lightweight models are well-suited for deployment on neuromorphic chips, enabling efficient inference.

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