Stand-Alone Inter-Frame Attention in Video Models

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Abstract

Motion, as the uniqueness of a video, has been critical to the development of video understanding models. Modern deep learning models leverage motion by either executing spatio-temporal 3D convolutions, factorizing 3D convolutions into spatial and temporal convolutions separately, or computing self-attention along temporal dimension. The implicit assumption behind such successes is that the feature maps across consecutive frames can be nicely aggregated. Nevertheless, the assumption may not always hold especially for the regions with large deformation. In this paper, we present a new recipe of inter-frame attention block, namely Stand-alone Inter-Frame Attention (SIFA), that novelly delves into the deformation across frames to estimate local self-attention on each spatial location. Technically, SIFA remoulds the deformable design via re-scaling the offset predictions by the difference between two frames. Taking each spatial location in the current frame as the query, the locally deformable neighbors in the next frame are regarded as the keys/values. Then, SIFA measures the similarity between query and keys as stand-alone attention to weighted average the values for temporal aggregation. We further plug SIFA block into ConvNets and Vision Transformer, respectively, to devise SIFA-Net and SIFA-Transformer. Extensive experiments conducted on four video datasets demonstrate the superiority of SIFA-Net and SIFA-Transformer as stronger backbones. More remarkably, SIFA-Transformer achieves an accuracy of 83.1% on Kinetics-400 dataset. Source code is available at https://github.com/FuchenUSTC/SIFA.

1. Introduction

Video is an electronic representation of moving visual images and naturally forms the motion, which signifies a continuous change in position of objects or persons with time. Modeling such temporal dynamics is essential to the extension from understanding still images to videos. The recent advances generally suggest to leverage motion along two directions. One involves utilization of temporal convolutions by being integrated into space-time 3D convolutions [18, 50] or explicitly co-working with spatial convolutions [3, 52, 62]. The other measures self-attention of each location over the temporal neighbors at the same spatial position across frames. Figure 1(a) and (b) conceptually depict the implementation of temporal convolution and self-attention along temporal dimension, respectively. The underlying spirit behind these operations originates from the foundation that the feature maps across frames should be well aligned. This assumption nevertheless may not always be valid in practice. Taking the three consecutive frames in Figure 1 as an example, the same positions across frames highlighted in the circles correspond to different objects (person and track in the case) due to the motion of the athlete in pole vault. As such, performing temporal convolution or computing attention over these positions might be suboptimal for temporal feature aggregation.

To alleviate this issue, we propose to take the changes
in video content caused by motion into account to enhance the alignment of feature maps across frames and eventually improve temporal aggregation. Technically, we develop inter-frame attention as shown in Figure 1(c) to characterize richer inter-frame correlation within a local neighboring region rather than only the same spatial location in consecutive frames. By doing so, inter-frame attention, on one hand, is beneficial more with large receptive fields, and on the other, manifests the emphasis of each location in the region to better achieve feature alignment. In an effort to nicely support the regions with large deformation, we further capitalize on the deformable design and estimate the offset to each spatial location. Moreover, we uniquely exploit the motion cues across frames to act as motion supervisory signal and re-scale the deformable feature re-sampling.

By delving into the deformation across frames to infer temporal attention within locally deformable region for temporal modeling, we present a novel Stand-alone Inter-Frame Attention (SIFA) block in video models. Specifically, we take each spatial location in the current frame as the query, and its temporal neighbors within the local region of the next frame are treated as keys/values accordingly to trigger the inter-frame attention learning. Note that in view of the irregular geometric transformations of objects, we sample the keys/values of temporal neighbors in a spatial deformation, which is learnt with additional guidance of the motion cues across frames. After that, SIFA block regards the estimated inter-frame attention of each temporal neighbor as its temporal correlation against query. Finally, we aggregate all temporal neighbors of nearby frames with inter-frame attention weights to further strengthen the query feature in current frame via temporal aggregation.

The SIFA block can be viewed as a stand-alone attention primitive for temporal modeling, and is readily pluggable to any 2D CNN or Vision Transformer backbones for video representation learning. By directly inserting SIFA block in ResNet [17] and Swin Transformer [32], we construct two new video backbones, named as SIFA-Net and SIFA-Transformer, respectively. Through extensive experiments on a series of action recognition benchmarks, we demonstrate that our SIFA-Net and SIFA-Transformer outperform several state-of-the-art video backbones.

2. Related Work

We categorize existing research for video representation learning into hand-crafted and deep model based methods.

**Hand-crafted Representation.** The early hand-crafted video feature techniques first detect spatio-temporal interest points and then describe them with local representations, such as STIP [23], Histogram of Gradient and Histogram of Optical Flow [24], 3D Histogram of Gradient [21], and SIFT-3D [45]. Besides, Wang et al. design the dense trajectory feature [54] that samples dense local patches from each frame at various scales and tracks them in an optical flow field to convey motion cues in temporal domain. Nevertheless, these hand-crafted features are not optimized, thereby hardly to be generalized across different video tasks.

**Deep Learning based Representation.** This direction first emerges by directly applying 2D CNN over video frames for video representation learning. For instance, Karpathy et al. stack frame-level CNN features in a fixed size of window and then leverage spatial convolution to learn video representation [20]. Later in [47], the two-stream model is devised by utilizing two 2D CNN separately on visual frames and stacked optical flows. This technique is further extended by exploring the convolution fusion [13], temporal segment networks [12, 57, 63] and convolutional encoding [6]. To capture the long-term temporal dependency which is commonly ignored in some two-stream networks, LSTM-based methods [40, 48] are designed to model long-range temporal dynamics in videos.

The aforementioned approaches only treat video as a sequence of frames or optical flows, while leaving the pixel-level temporal evolution across consecutive frames unexploited. 3D CNN based video feature [50] is thus proposed to alleviate this issue by employing 3D convolutional kernels over short clips. Furthermore, the subsequent works [3, 41, 43, 62, 64] show that factorizing 3D convolution into 2D spatial convolution and 1D temporal convolution leads to better results and presents good generalization ability on localization task [25, 26, 35–37]. Most recently, inspired by the impressive performances of applying self-attention from NLP field [53] into image feature learning [7, 29, 32], TimeSformer [2] performs self-attention along the temporal dimension and designs five variants for temporal modeling. Nevertheless, these methods equipped with temporal convolution or temporal self-attention still suffer from the robustness problem due to object deformation across frames.

Our work belongs to deep model based techniques that model temporal dynamics through self-attention. Unlike TimeSformer [2] that measures self-attention of each location solely over its temporal neighbors at the same spatial location, SIFA mechanism performs inter-frame attention within a local neighboring region with large receptive fields. Moreover, SIFA block goes beyond the measure of inter-frame self-attention within regular local region, and capitalizes on locally deformable neighbors to tackle the irregular object deformation issue in temporal modeling.

3. Our Approach

We introduce a new Stand-alone Inter-Frame Attention (SIFA) for temporal modeling. SIFA exploits the temporal correlation within local region across consecutive frames, aiming to strengthen per-frame feature by aggregating its local neighbors in nearby frames via attention. Next, a novel stand-alone block in video models, i.e., SIFA block,
As depicted in Figure 2 (a). Technically, let \( F \) be the input 3D feature map with the size of \( C \times L \times H \times W \), where \( C \), \( H \times W \), and \( L \) denotes the channel size, spatial size, and temporal length, respectively. We first reshape \( F \) into a 2D feature sequence \( \{ f_t \}_{t=0}^{L-1} \). Next, for \( t \)-th frame, we take its feature at the spatial location \( (x, y) \) as the query \( Q_t \in \mathbb{R}^C \). Meanwhile, the features of \((t+1)\)-th frame within the local region (size: \( k \times k \) grid) centered at \( (x, y) \) are set as keys \( K_{t+1} \in \mathbb{R}^{C \times \{k \times k\}} \) and values \( V_{t+1} \in \mathbb{R}^{C \times \{k \times k\}} \). The correlation matrix \( W_{cor} \) between query \( Q_t \) and keys \( K_{t+1} \) is then calculated via dot production:

\[
W_{cor} = Q_t \odot K_{t+1},
\]

where \( \odot \) denotes the matrix multiplication that measures the pairwise temporal correlation between query and its temporal neighbors (i.e., keys) within the local \( k \times k \) grid.

Existing works commonly take the learnt correlation matrix \( W_{cor} \in \mathbb{R}^{1 \times \{k \times k\}} \) as pixel-level displacement information, and directly augment primary feature map with it to subserve flow estimation [14, 61], geometric matching [44] and motion modeling [55]. As an alternative, we capitalize on the correlation matrix as attention weights to dynamically aggregate the corresponding values within local region in nearby frame, targeting for enhancing query feature. In particular, by taking the correlation matrix \( W_{cor} \) as the attention weights, the values \( V_{t+1} \) within the local region are aggregated in a channel-wise manner:

\[
A_{t+1} = W_{cor} \odot [V_{t+1}]^T,
\]

where \( A_{t+1} \) is the aggregated feature derived from the temporal neighbors of query, and the \([\cdot]^T\) denotes the matrix transpose. After that, we integrate the query with the aggregated feature, yielding the enhanced query feature \( Y_t \) after temporal feature aggregation:

\[
Y_t = Q_t + A_{t+1}.
\]

Accordingly, SIFA performs the inter-frame attention over each spatial location in \( t \)-th frame to mine its temporal correlation within local region of \((t+1)\)-th frame. The feature map of each frame is thus strengthened by aggregating the features of local neighbors in the next frame via attention. In this way, we operate SIFA between every pair of adjacent frames in the input sequence. Note that for the last frame in the sequence, we conduct the inter-frame attention between this frame and itself, and enhance its feature map by itself through feature aggregation, thereby keeping the temporal length of output frame sequence as \( L \).

Connections with Previous Spatio-temporal Attention. Here we further discuss the detailed relations and differences between our SIFA and the previous spatio-temporal attention mechanisms. [2] introduces two kinds of spatio-temporal attention (i.e., joint or divided spatio-temporal self-attention) that employ self-attention over space and time for video representation learning. Specifically, the joint spatio-temporal self-attention (i.e., ST in
Figure 2 (b)) performs self-attention over the input features/patches of all frames holistically. The divided spatio-temporal self-attention (i.e., T+S in Figure 2 (c)) separately applies the spatial attention within current frame and the temporal attention over the temporal neighbors in the same spatial location of nearby frames. Our SIFA also targets for exploring self-attention along temporal dimension for video modeling. Different from the global temporal attention over the holistic features/patches in ST, SIFA conducts the local temporal attention within local region across frames, which is computationally more efficient. Moreover, compared to S+T that only mines temporal evolution in the same spatial location of consecutive frames, SIFA captures the richer inter-frame correlation within local region for attention learning, thereby facilitating temporal modeling.

3.2. SIFA Block

Recall that our SIFA mechanism is devised to model the temporal evolution of objects within local region across consecutive frames. However, simply employing inter-frame attention over the equally-sized local region ($k \times k$ grid) inevitably ignores the irregular geometric transformations of objects in each frame, resulting in a sub-optimal solution. To alleviate this issue, we devise a SIFA block that applies inter-frame attention over the locally deformable region in nearby frames, which consists of the temporal neighbors sampled in a free-form spatial deformation.

The most typical way to operate deformable feature re-sampling is to augment the spatial sampling locations with additional offsets, that are predicted via a learnable offset estimator as in deformable ConvNets [5]. Nevertheless, this offset estimator learns to infer the 2D offset of each spatial location solely based on the input feature map itself, while leaving the inherent motion clues across consecutive frames unexploited. Instead, we propose to estimate 2D offset of each spatial location within local region based on its motion saliency map (MSM), which acts as motion supervision to guide the deformable feature re-sampling. Figure 3 shows the detailed structure of our SIFA block.

Formally, given each pair of consecutive frames (i.e., $t$-th frame $f_t$ and $(t+1)$-th frame $f_{t+1}$), we first compute the temporal difference (TD) in between:

$$\Delta f = f_{t+1} - f_t.$$  \hspace{1cm} (4)

Next, we employ a sigmoid operation over such temporal difference, leading to a normalized attention map. This attention map dynamically pinpoints the spatial locations in $(t+1)$-th frame that contain highly salient movements of objects. Therefore, the motion saliency map (MSM) $f_m$ is achieved by multiplying the feature map of $(t+1)$-th frame $f_{t+1}$ with the attention map:

$$f_m = \text{sigmoid}(\Delta f) * f_{t+1}.$$  \hspace{1cm} (5)

Conditioned on the motion saliency map $f_m$, we utilize an offset estimator to predict the 2D offset for each spatial location within the local region ($k \times k$ grid) of $(t+1)$-th frame $f_{t+1}$. Note that the offset estimator is implemented as a 2D convolutional layer with the output channel size of $2k^2$. More specifically, let $(\Delta a, \Delta b)$ denote the estimated 2D offset of each spatial location $p = (a, b)$ within the $k \times k$ grid centered at the query location $(x, y)$. The corresponding irregular spatial location is thus represented as $p' = (a + \Delta a, b + \Delta b)$. Following [5], we sample the feature $K'_{t+1}(p')$ at each irregular spatial location $p'$ through bilinear interpolation:

$$K'_{t+1}(p') = \sum_p G(p, p') \cdot K_{t+1}(p),$$  \hspace{1cm} (6)

where $p'$ is the fractional spatial location and $p$ enumerates all integral spatial locations within the local region. $K_{t+1}(p)$ denotes the primary feature at regular spatial location $p$, and $G$ is bilinear interpolation kernel. After sampling all the $k^2$ deformable features in $(t+1)$-th frame $f_{t+1}$, we take them as the keys $K'_{t+1} \in \mathbb{R}^{C \times (k \times k)}$ and values $V'_{t+1} \in \mathbb{R}^{C \times (k \times k)}$ with regard to the query $Q_t \in \mathbb{R}^C$ in $t$-th frame $f_t$. In this way, we perform SIFA mechanism over the locally deformable region in nearby frame, and further strengthen per-frame feature by aggregating these deformable features via attention:

$$W_{cor} = Q_t \odot K'_{t+1},$$
$$A_{t+1} = W_{cor} \odot [V'_{t+1}]^T,$$
$$Y_t = Q_t + A_{t+1}.$$  \hspace{1cm} (7)

The enhanced feature $Y_t$ for $t$-th frame is finally taken as the output of SIFA block.

3.3. 2D CNN and Vision Transformer with SIFA

Our SIFA block acts as a stand-alone primitive for temporal modeling, and is pluggable to any 2D CNN or Vision Transformer architectures. Such design naturally upgrades these vision backbones with the capacity of temporal modeling, thereby boosting video representation learning. Here we present how to integrate SIFA block into existing 2D CNN (e.g., ResNet [17]) and Vision Transformer...
In this section, we perform a series of ablation studies to examine several technical choices of our proposed Stand-alone Inter-Frame Attention (SIFA) block in SIFA-Net. Specifically, the deep architecture of SIFA-Net is constructed based on the backbone of ResNet-50, and we report the top-1 and top-5 accuracy on the validation set of Kinetics-400 for performance comparison.

**Stand-alone Inter-Frame Attention.** We first investigate how each design in our SIFA block influences the overall performance of SIFA-Net. Table 1a details the performance comparisons among different variants of SIFA block. Note that all ablated runs here are constructed by only plugging the SIFA variants into the building blocks at res5 stage.
Table 1. Ablation study on SIFA block in SIFA-Net with 16-frame inputs on Kinetics-400 dataset. Top-1 and Top-5 accuracy (%), and the computational cost (measured in GFLOPs) for forwarding one clip at inference are reported.

(a) **Stand-alone Inter-Frame Attention.** Comparisons among different variants of SIFA. All runs are constructed by plugging each block into res5 stage of ResNet-50.

| Model       | GFLOPs | Top-1 | Top-5 |
|-------------|--------|-------|-------|
| 2D-ResNet   | 23     | 72.0  | 90.3  |
| SIFA_C      | 23     | 73.3  | 90.8  |
| SIFA_R      | 24     | 74.6  | 91.5  |
| SIFA        | 24     | 75.4  | 92.9  |

(b) **Deformable Offset.** Comparisons across different ways on the measure of deformable offset in SIFA block. All runs are constructed by plugging each block into res5 stage of ResNet-50.

| Offset       | GFLOPs | Top-1 | Top-5 |
|--------------|--------|-------|-------|
| Regular (SIFA_R) | 24     | 74.6  | 91.5  |
| Conv2D($f_{t+1}$) | 24     | 74.7  | 91.6  |
| Conv2D($f$)   | 27     | 74.8  | 91.9  |
| Conv2D($\Delta f$) | 24     | 75.0  | 92.1  |
| Conv2D($m$) (SIFA) | 24     | 75.4  | 92.9  |

(c) **Local Region Size.** Comparisons by using different local region size $k$. All runs are constructed by plugging each block into res5 stage of ResNet-50.

| Size $k$ | GFLOPs | Top-1 | Top-5 |
|----------|--------|-------|-------|
| 1 x 1    | 24     | 73.4  | 90.9  |
| 3 x 3    | 24     | 75.4  | 92.9  |
| 5 x 5    | 25     | 75.4  | 93.0  |
| 7 x 7    | 26     | 75.4  | 93.0  |
| 9 x 9    | 29     | 75.5  | 93.1  |

(d) **Location of SIFA Block in SIFA-Net.** Effect of plugging SIFA block into different stages of ResNet-50.

| Stage | GFLOPs | Top-1 | Top-5 |
|-------|--------|-------|-------|
| SESA2 | 23     | 72.0  | 90.3  |
| SESA3 | 24     | 75.4  | 92.9  |
| SESA4 | ✓      | 24    | 76.2  | 93.0  |
| SESA5 | ✓ ✓    | 25    | 77.4  | 93.3  |
| SESA5 | ✓ ✓ ✓  | 26    | 77.4  | 93.2  |

(e) **Temporal Modeling.** Comparisons with different temporal modeling techniques (backbone: ResNet-50).

| Temporal Modeling | GFLOPs | Top-1 | Top-5 |
|-------------------|--------|-------|-------|
| 2D-ResNet         | 23     | 72.0  | 90.3  |
| Temporal Conv [52] | 33     | 74.1  | 91.4  |
| Temporal Shift [30] | 23     | 74.7  | 91.4  |
| Correlation [55]  | 23     | 75.1  | 91.6  |
| Temporal Difference [56] | 36    | 76.6  | 92.8  |
| SIFA              | 25     | 77.4  | 93.3  |

GFLOPs version of our SIFA block, i.e., finally achieves 75.5%. In addition, we include an upgraded object motion modeling techniques (backbone: ResNet-50).

The result basically validates the effectiveness of deformable feature re-sampling. Compared to Conv2D($f_{t+1}$) that predicts the deformable offsets of each frame independently, Conv3D($f$) jointly infers the offset of each spatial location based on the holistic feature sequence, and thus achieves better performances, while requiring more computational cost. Instead of using 3D convolution to capture motion clues for offset prediction in Conv3D($f$), Conv2D($\Delta f$) explicitly utilizes the temporal difference between consecutive frames to estimate 2D offset via 2D convolution, leading to performance improvements in an efficient way. Furthermore, by integrating the feature map of the next frame with the inter-frame motion saliency map for offset prediction, Conv2D($m$) (i.e., our SIFA) obtains the highest performances.

**Local Region Size.** To explore the effect of local region size $k$ for inter-frame attention learning in SIFA block, we evaluate the performance and computational cost by varying $k$ from 1 to 9 with an interval of 2 in Table 1c. In the extreme case of $k = 1$, only a single temporal neighbor at the same spatial location of nearby frame is taken as key to measure inter-frame attention. As such, the SIFA block degenerates to temporal convolution that only explores temporal evolution in the same spatial location across frames. With the use of larger local region size ($k = 3$), the top-1 accuracy is significantly increased from 73.4% to 75.4%. That basically validates the merit of performing inter-frame attention over locally deformable region across consecutive
Table 2. Performance comparisons on Kinetics-400. The input clip length of SIFA-Net is shown inside the bracket.

| Approach            | Backbone | GFLOPs/× views | Top-1 | Top-5 |
|---------------------|----------|----------------|-------|-------|
| Convolutional Networks |          |                |       |       |
| I3D [1]             | Inception | 108×N/A       | 72.1  | 90.3  |
| TSN [57]            | R50      | 80×10         | 72.5  | 90.2  |
| MF-Net [4]          | R50      | 11×50         | 72.8  | 90.4  |
| R2+4-ID [52]        | R50      | 152×10        | 74.3  | 91.4  |
| S3D [62]            | R50      | 71×30         | 74.7  | 93.4  |
| TSM [30]            | R50      | 33×30         | 74.1  | 91.2  |
| TEINet [33]         | R50      | 33×30         | 74.9  | 91.8  |
| TEA [24]            | R50      | 33×30         | 75.0  | 91.8  |
| SlowFast [11]       | R50×R50  | 36×30         | 75.6  | 92.1  |
| NL I3D [58]         | R50      | 282×30        | 76.5  | 92.6  |
| SmallBig [27]       | R50      | 57×30         | 76.3  | 92.5  |
| CorrNet [55]        | R50      | 115×10        | 77.2  | -     |
| TDN [50]            | R50      | 72×30         | 77.5  | 93.2  |
| SIFA-Net (16)       | R50      | 25×30         | 77.4  | 93.3  |
| SIFA-Net (32)       | R50      | 51×30         | 78.5  | 93.6  |
| SIFA-Net (64)       | R50      | 112×30        | 80.1  | 94.4  |
| ip-CSN [51]         | R101     | 83×30         | 76.7  | 92.3  |
| SmallBig[27]        | R101     | 418×12        | 77.4  | 93.3  |
| NL I3D [38]         | R101     | 359×30        | 77.7  | 93.3  |
| TDN [50]            | R101     | 132×30        | 78.5  | 93.9  |
| CorrNet [55]        | R101     | 224×30        | 79.2  | -     |
| SlowFast [11]       | R101+R101| 234×30        | 79.8  | 93.9  |
| SIFA-Net (16)       | R101     | 39×30         | 78.7  | 94.0  |
| SIFA-Net (32)       | R101     | 78×30         | 79.8  | 94.2  |
| SIFA-Net (64)       | R101     | 157×30        | 81.3  | 95.2  |
| Vision Transformer  |          |                |       |       |
| TimeSformer [2]     | ViT-B    | 2,380×3       | 80.7  | 94.7  |
| ViViT [1]           | ViT-L    | 3,992×12      | 81.3  | 94.7  |
| MVIT [8]            | ViT-B    | 455×9         | 81.2  | 95.1  |
| Video-Swin [34]     | Swin-B   | 282×12        | 82.7  | 95.5  |
| SIFA-Transformer    | Swin-B   | 270×12        | 83.1  | 95.7  |

Table 3. Performance comparisons on Kinetics-600. The input clip length of SIFA-Net is shown inside the bracket.

| Approach            | Backbone | GFLOPs/× views | Top-1 | Top-5 |
|---------------------|----------|----------------|-------|-------|
| Convolutional Networks |          |                |       |       |
| I3D [1]             | Inception | 108×N/A       | 71.9  | 90.1  |
| SlowFast [11]       | R50×R50  | 36×30         | 78.8  | 94.0  |
| SIFA-Net (16)       | R50      | 25×30         | 79.6  | 94.5  |
| SIFA-Net (32)       | R50      | 51×30         | 80.5  | 95.2  |
| SIFA-Net (64)       | R50      | 112×30        | 82.1  | 95.8  |
| SlowFast [11]       | R101+R101| 234×30        | 81.8  | 95.1  |
| X3D-XL [10]         | R101     | 49×30         | 81.9  | 95.5  |
| SIFA-Net (16)       | R101     | 39×30         | 80.8  | 95.2  |
| SIFA-Net (32)       | R101     | 78×30         | 81.6  | 95.5  |
| SIFA-Net (64)       | R101     | 157×30        | 83.2  | 95.9  |
| Vision Transformer  |          |                |       |       |
| TimeSformer [2]     | ViT-B    | 1,703×3       | 82.4  | 96.0  |
| ViViT [1]           | ViT-L    | 3,992×12      | 83.0  | 95.7  |
| MVIT [8]            | ViT-B    | 236×5         | 83.8  | 96.3  |
| Video-Swin [34]     | Swin-B   | 282×12        | 84.0  | 96.5  |
| SIFA-Transformer    | Swin-B   | 270×12        | 84.5  | 96.9  |

4.3. Comparisons with State-of-the-Art Methods

We compare SIFA-Net and SIFA-Transformer with various state-of-the-art techniques on Kinetics-400, Kinetics-600, and Something-Something V1 (SSv1) and V2 (SSv2) datasets. All runs are briefly grouped into two paradigms: Convolutional Networks and Vision Transformer. Note that we implement SIFA-Net in two kinds of backbones, i.e., ResNet-50 (R50) and ResNet-101 (R101), and the input clip length is varied in the range of \{16, 32, 64\}. The SIFA-Transformer is constructed based on the backbone of Swin Transformer (Swin-B) with the fixed input clip length (64 frames). The computational cost is measured in GFLOPs×views, and the views represent the number of clips sampled from the full video at inference.

Table 2 summarizes the performance comparisons on Kinetics-400. For the group of Convolutional Networks, our SIFA-Net leads to better performances against other baselines. In particular, SIFA-Net (32) in R50 backbone obtains 78.5% top-1 accuracy, and outperforms the best competitor TDN by 1.0% but with \sim 30% less computation cost in GFLOPs. By sampling more frames in each clip for temporal modeling, SIFA-Net (64) improves the top-1 accuracy from 78.5% to 80.1%. The superior results of SIFA-Net generally demonstrate the advantage of integrating 2D CNN with inter-frame attention to enable temporal aggregation. In particular, by explicitly capturing motion displacement across frames, Correlation [55] outperforms Temporal Conv [52]. Temporal Difference [56] further boosts the performances by additionally modeling long-term motion. Nevertheless, the performances of Temporal Difference are still lower than that of our SIFA which exploits inter-frame attention for temporal modeling.
### 4.4. Visualization Analysis of SIFA

To better qualitatively examine SIFA block for video representation learning, we further visualize the inter-frame attention map over the locally deformable region, motion saliency map (MSM) and the class activation map with Grad-CAM [46] of SIFA-Net for three videos in Kinetics-400. For the video in each row, the green point in its $t$-th frame denotes the query location. The correlation between query and sampling points in $(t+1)$-th frame (i.e., attention weight) is shown in heat map. We link the query and sampling points with top-3 attention weights in purple line. The red box in MSM represents the region with highly salient object movements. Re-sampling with MSM, the sampling points are nicely adjusted according to the objects’ scale, irregular shape, and large movements. This again confirms that SIFA block takes the object movement and deformation across frames into account to strengthen inter-frame feature alignment, thereby boosting temporal modeling.

#### 5. Conclusions and Discussions

We have presented Stand-alone Inter-Frame Attention (SIFA) block, which explores the deformation across frames for temporal modeling with local self-attention. Specifically, by taking the spatial location in current frame as query, SIFA performs self-attention over the keys/values in a local neighboring region of next frame. Moreover, to tackle the irregular object deformation in next frame, a deformable design is leveraged to estimate the offset of each spatial location in local region, yielding the keys/values re-sampled in a deformation. Such deformable feature re-sampling is additionally re-scaled by motion cues to facilitate inter-frame attention learning. Finally, all deformable values are aggregated with attention to enhance per-frame feature. By plugging SIFA block into ResNet and Swin Transformer, we construct two new video backbones (SIFA-Net and SIFA-Transformer), and the experiments on four action recognition datasets demonstrate their effectiveness.

#### Broader Impact

One negative impact of this research in video representation learning is the significant environmental impact associated with training Transformer backbones, which are large and computationally expensive. There is also potential for these action recognition models to be misused, such as for unauthorized surveillance.

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**Table 4. Performances on Something-Something V1 and V2.** The input clip length of SIFA-Net is shown inside the bracket.

| Approach       | Backbone | GFLOPs (× views) | SSv1 Top-1 | SSv1 Top-5 | SSv2 Top-1 | SSv2 Top-5 |
|----------------|----------|------------------|------------|------------|------------|------------|
| **Convolutional Networks** |          |                  |            |            |            |            |
| NL/3D+GEN [59] | R50      | 608              | 46.1       | 76.8       | -          | -          |
| CPNet [31]    | R34      | N/A              | -          | -          | 57.7       | 84.0       |
| TSM [30]      | R50      | 98               | 47.2       | 77.1       | 63.4       | 88.5       |
| TAM [19]      | R50      | 48               | 48.4       | 78.8       | 61.7       | 88.1       |
| GST [39]      | R50      | 59               | 48.6       | 77.9       | 62.6       | 87.9       |
| SmallBig [27] | R50      | 105              | 49.3       | 79.5       | 62.3       | 88.5       |
| CorrNet [55]  | R50      | 115×10           | 49.3       | -          | -          | -          |
| ACTION-Net [60]| R50      | 69               | -          | -          | 64.0       | 89.3       |
| STM [19]      | R50      | 67×30            | 50.7       | 80.4       | 64.2       | 89.8       |
| MSNet [22]    | R50      | 67               | 52.1       | 82.3       | 64.7       | 89.4       |
| TEINet [33]   | R50      | 99               | 52.5       | -          | 65.5       | 89.8       |
| MG-TEA [65]   | R50      | N/A              | 53.2       | -          | 63.8       | -          |
| TDN [56]      | R50      | 72               | 53.9       | 82.1       | 65.3       | 89.5       |
| SIFA-Net (16) | R50      | 25×3             | 52.7       | 81.9       | 64.8       | 89.4       |
| SIFA-Net (32) | R50      | 51×3             | 54.0       | 82.2       | 66.0       | 89.6       |
| SIFA-Net (64) | R50      | 112×3            | 55.2       | 83.3       | 66.9       | 90.7       |
| GSM [29]      | Inception | 268              | 55.2       | -          | -          | -          |
| CorrNet [55]  | R101     | 224×30           | 53.3       | -          | -          | -          |
| MG-TEA [65]   | R101     | N/A              | 53.3       | -          | 64.8       | -          |
| TDN [56]      | R101     | 132×3            | 53.3       | 83.3       | 66.9       | 90.9       |
| SIFA-Net (16) | R101     | 397×3            | 53.7       | 82.0       | 65.9       | 89.8       |
| SIFA-Net (32) | R101     | 78×3             | 55.4       | 83.1       | 67.3       | 91.1       |
| SIFA-Net (64) | R101     | 157×3            | 56.1       | 84.0       | 68.1       | 92.0       |
| **Vision Transformer** |          |                  |            |            |            |            |
| TimeFormer [2] | ViT-B    | 1,703×3          | -          | -          | 62.5       | -          |
| ViOVT [1]     | ViT-L    | 903              | -          | -          | 65.4       | 89.8       |
| MVT [8]       | ViT-B    | 455×3            | -          | -          | 67.7       | 90.9       |
| Video-Swin [33]| Swin-B   | 321×3            | -          | -          | 69.6       | 92.7       |
| SIFA-Transformer | Swin-B | 270×3            | 57.3       | 85.1       | 69.8       | 93.1       |

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**Figure 5.** Visualization of the inter-frame attention map, motion saliency map (MSM) and Grad-CAM [46] of SIFA-Net for three videos in Kinetics-400.
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