Self-supervised learning has shown great potentials in improving the deep learning model in an unsupervised manner by constructing surrogate supervision signals directly from the unlabeled data. Different from existing works, we present a novel way to obtain the surrogate supervision signal based on high-level feature maps under consistency regularization. In this paper, we propose a Spatio-Temporal Consistency Regularization between different output features generated from a siamese network including a clean path fed with original video and a noise path fed with the corresponding augmented video. Based on the Spatio-Temporal characteristics of video, we develop two video-based data augmentation methods, i.e., Spatio-Temporal Transformation and Intra-Video Mixup. Consistency of the former one is proposed to model transformation consistency of features, while the latter one aims at retaining spatial invariance to extract action-related features. Extensive experiments demonstrate that our method achieves substantial improvements compared with state-of-the-art self-supervised learning methods for action recognition. When using our method as an additional regularization term and combine with current surrogate supervision signals, we achieve 22% relative improvement over the previous state-of-the-art on HMDB51 and 7% on UCF101.

**Keywords** self-supervised · consistency regularization · data augmentation

1 Introduction

Convolutional neural networks (CNNs) can achieve competitive accuracy on a variety of video understanding tasks, including action recognition [1], temporal action detection [2] and spatio-temporal action localization [3]. Such success is built on the heavily annotated datasets, which are time-consuming and expensive to obtain. Since numerous unlabeled data is instantly available (e.g. online video sequences), it has drawn more and more attention from the community to utilize the off-the-shelf unlabeled data to improve the performance of CNNs.

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Self-supervised learning aims at resolving the designed pretext tasks which can be formulated using only unlabeled data [4]. Without huge human efforts for annotation, surrogate supervision signals can be used to pretrain the CNNs with the pretext tasks. For instance, the relative positions of image patches [5] and image rotation degrees [6] are used as surrogate supervision signals to learn semantic features for better image classification.

Besides image applications, self-supervised learning has been extended to video applications especially action recognition. Using temporal information in videos, recent works attempt to perform temporal modeling among frames via specifically designed supervision signals, such as the arrow of time [7] or the clip order [8]. However, current video datasets usually exist large implicit biases over scene and object structure, which makes the temporal structure become less insignificant. Consequently, these methods may focus on appearance information rather than useful video representation.

To overcome this limitation, we propose a novel surrogate supervision signal based on consistency regularization of spatially and temporally augmented data. In the proposed method, data augmentation is applied to the original input. Then the original and augmented videos are fed into the siamese CNN which is trained to minimize the mean-square error (MSE) between the corresponding features of the original and augmented videos. By this way, a new pretext task can be defined for pretraining using the augmented data. As a result, data augmentation becomes a very important component in the proposed pretext task to extract discriminative features for action recognition. Based on the Spatio-Temporal characteristics of video, this paper proposes Spatio-Temporal Transformation and Intra-Video Mixup as shown in Figure 1 for data augmentation. By minimizing the MSE between the features of the original and augmented videos, a CNN model can be pretrained semantically in two aspects, i.e., robustness to transformation and spatial invariance.

Experimental results show that the proposed self-supervised learning approach using consistency regularization provides a powerful surrogate supervision signal for semantic feature learning and leads to dramatic improvements on action recognition benchmarks. By incorporating the proposed consistency regularization into existing self-supervised learning methods, performance can be further improved. The major contributions of this paper are summarized as follows:

- We propose a novel consistency regularization of spatially and temporally augmented data, which can be served as a new supervised signal under the self-supervised framework and can easily improve existing methods for action recognition.
We propose two novel data augmentation methods, Spatio-Temporal Transformation and Intra-Video Mixup, for transformation consistency and spatial invariance in video-based self-supervised learning.

Our proposed method outperforms state-of-the-art methods on UCF101 [9] and HMDB51 [10].

2 Related Work

2.1 Self-supervised Learning

Self-supervised learning is a generic learning framework that relies on proxy tasks that can be formalized using only unsupervised data. Gidaris et al. [6] use the prediction of image rotation as training target while we just use Spatial Rotation as perturbation to make model more robust. Meng et al. [11] adopt simease network and adopt image instance classification but we focus on video domain. More recently, this valuable research has expanded into video domain. The related work [8] predicts video clip order or learning the arrow of time [7, 12]. However, these methods are specially designed without generalization, which is our focus.

2.2 Consistency Regularization

Consistency regularization applies data augmentation to semi-supervised learning, which takes advantage of the idea that a classifier should output the same class distribution for an unlabeled example even it has been augmented. There are many semi-supervised learning based on consistency regularization in general [13, 14, 15, 16]. In this work, we propose a novel form of consistency regularization through the use of Spatio-temporal Transformation and Intra-Video Mixup. To our best knowledge, we are the first one that introduce consistency regularization into self-supervised learning.

Our motivation is also different from [17] which involves geometric transformation in attention consistency under fully supervised setting. Note that, keeping visual attention consistency relies on the class activation map (CAM) [18] which needs category annotations. While, we restrain high-level feature map without using CAM. Otherwise, we add constraint along the temporal dimension rather than pixel-wise in spatial.

2.3 Data Augmentation

In image classification, the input image will usually undergo elastic deformation or add noise, which can greatly change the pixel content of the image without changing the label. Based on this, a lot of augmentation technologies include rotation, flip and color jittering [19] has been proposed. Recently, Mixup [20] is a practical data augmentation method in image classification that combines two samples, the ground-truth label of the new sample is given by the linear interpolation of one-hot labels.

However, Mixup requires both label and pair samples in a batch during train. In contrast, Intra-Video Mixup selects one frame from the video itself and doesn’t label under the framework of consistency learning, which can be integrated into unsupervised or semi-supervised learning.

3 Methodology

In this section we present the proposed Spatio-Temporal Consistency Regularization (STCR) for action recognition. We first give an overall description of STCR in Section 3.1. Then, details about Spatio-Temporal Data Augmentation and Consistency Regularization are introduced in Section 3.2 and Section 3.3. At last, we discuss the advantages of STCR in Section 3.4.

3.1 Overall Architecture

The framework of the proposed self-supervised learning method is shown in Figure 2. The trunk of our framework is a siamese network with two branches (named as Clean Path and Noise Path). Each branch contains a conventional 3D backbone, and the parameters of the backbone between all branches are shared and recorded as $\theta$. For each input $x$, these two branches randomly crop a fixed-length clip of video frames from different spatial locations, denoted as $x^c$ and $x^n$. In this way, the input frames between these two branches get different distribution in pixel level but consistent in semantic level.

After that, we directly feed the inputs $x^c$ into the Clean Path and we perform Spatio-Temporal Transformation and Intra-Video Mixup on inputs $x^n$ for Noise Path. The output of these two branches are represented as $f_{x^c}, f_{x^n} \in$
Figure 2: Framework of the proposed method for training. The input videos are projected into high-level feature maps with the CNN backbone. The augmented video is constrained to be consistent with the original video in both temporal direction and channel. (Best viewed in color).

$\mathbb{R}^{C' \times T' \times H' \times W'}$, formally written as:

$$f_{x} = F(x; \theta)$$  \hspace{0.5cm}  (1)  

$$f_{x^n} = F(\phi(T(x^n)); \theta)$$  \hspace{0.5cm}  (2)  

where $F(\cdot; \theta)$ represents the siamese branch with parameter $\theta$, $T$ represents Spatio-Temporal Transformation and $\phi$ represents Intra-Video Mixup. $C'$ is the number of channel and $T'$ is the length of time dimension, $W'$ and $H'$ is the spatial size.

At last, these extracted features are fed into the regularization head and pretext task head which can be any usual self-supervised learning setting, such as predicting the arrow of time. For the Temporal Consistency Regularization, we minimize the gap of high-level features between the Clean Path and Noise Path with additional corresponding inverse transformation. The Algorithm 1 in Supplementary Section 2 summarizes the proposed method.

### 3.2 Spatio-Temporal Data Augmentation

#### 3.2.1 Spatio-Temporal Transformation

There are two targets throughout the design of Spatio-Temporal Transformation, the network must able to learn the potential temporal patterns and the learning process are robust to the spatial variations in frames. Designed with these objectives in mind, the proposed Spatio-Temporal Transformation $T$ is implemented via the Rotation or Flip on input clips. More specifically, for a random input clip $X$, we random choose Flip operator $z_1$ from set $F$ {No Flip, Left-right Flip, Temporal Flip, Temporal Flip + Left-right Flip} and Rotation degrees $z_2$ from set $R$ {0°, 90°, 180°, 270° }. The total combinations $L$ is $4 \times 4 = 16$, as shown in Figure 3. For an input clip $x^n$ with random combination $(z_1, z_2)$, formally,

$$T(x^n) = \text{Rot} (\text{Flip}(x^n), z_1), z_2$$  \hspace{0.5cm}  (3)  

where $\text{Rot}$ is the rotation operator and $\text{Flip}$ is the Flip operator. All these operators process all frames in the same way throughout the entire video clip.

#### 3.2.2 Intra-Video Mixup

Intra-Video Mixup is proposed to learn the desired semantic structure and to avoid the network focus on low-level visual clues which might cause the degradation of performance. Hence, Intra-Video Mixup aims at generating new training data by adding static spatial perturbation without changing its motion pattern.
Figure 3: An illustration of Spatio-Temporal Transformation (STT) and Intra-Video Mixup (IM). STT include four types of flip and each kind of flip corresponding to four types of rotation. STT encourages base encoder keep the direction of motion information in high-level feature map. IM encourages the model be not sensitive to static spatial appearance and focus more on dynamic motion information.

More specifically, for training sample \( x^n \) we random select one frame \( x^n_k \) from itself and then combine them, defined as:

\[
\phi(x^n_j) = (1 - \lambda) \cdot x^n_j + \lambda \cdot x^n_k, j \in [1, T]
\]

where \( \lambda \) is sampled from the beta distribution Beta(\( \alpha, \alpha \)), \( j \) is the index of frame and \( k \) denote the index of random selected frame. An intuitive example is shown in Figure 3.

### 3.3 Spatio-Temporal Consistency Regularization

The design of STCR has two objectives: First, since our purpose is to learn a semantic relevant CNN with given Pretext task, the STCR should introduce learnable parameters as few as possible. Second, the network should focus more on temporal aspect but robust to spatial noise. To achieve these goals, STCR includes two parts: temporal-wise and channel-wise constrains.

In particular, we introduce inverse transform \( F^{-1} \) on \( f_{x^n} \) to align the feature from Clean and Noise Path, which simply reverse the operation of Spatio-Temporal Transformation. Since temporal information play a key role in video representation, we first encourage Noise Path and Clean Path keep identify temporally.

Formally, \( L_{tw} = ||\psi(f_{x^n_c}) - \psi(T^{-1}(f_{x^n_n}))||^2 \) (5)

where \( \psi \) is the explicit feature mapping function from high-level feature map with shape \( \mathbb{R}^{C' \times T' \times H' \times W'} \) to \( \mathbb{R}^{C' \times T'} \) that keep temporal dimension. As Noise Path and Clean Path are randomly cropped from different spatial location from same video, we select no-parameter spatial global max pooling layer as \( \psi \). In this way, we only force the max response along each time dimension to be similar.

However, although the majority of Clean Path and Noise Path in spatial dimension is identical, there may still exist some special cases: key motion area is preserved in one path but missing in another path. In addition, keeping consistent under Spatio-Temporal Transformation along each time dimension may be hard to learn at the beginning of training. To address these problems, we propose a channel-wise constrain which is more easy to optimize. This constrain further reduce the temporal dimension via learnable transformation. In this way, the input video clip is encoded into a descriptor with shape \( C' \). And we compute \( L_{cw} \) by

\[
L_{cw} = KL(\mathcal{H}(\psi(f_{x^n_c}); W^1_c), \mathcal{H}(\psi(T^{-1}(f_{x^n_n})); W^2_c))
\]

where \( \mathcal{H} \) is a non-linear mapping with parameter \( W_c \) and \( KL \) means Kullback–Leibler divergence. The overall loss includes two terms:

\[
\mathcal{L} = L_{tw} + \gamma L_{cw}
\]

To combine these terms, we scale the latter by \( \gamma \).
| Method       | Top-1 accuracy (%) |
|--------------|---------------------|
| Baseline     | 24.2                |
| Gaussian Noise | 25.8               |
| Video Mixup  | 23.1                |
| Video CutMix | 24.0                |
| Inter-Video Mixup | 28.0            |
| Intra-Video Mixup | 30.2             |

Table 1: Comparison Intra-Video Mixup with other methods.

| STT | IM | UCF101(%) | HMDB51(%) |
|-----|----|-----------|-----------|
| ✓   | ✓  | 60.3      | 24.2      |
| ✓   | ✓  | 63.2      | 27.9      |
| ✓   | ✓  | 64.3      | 30.3      |
| ✓   | ✓  | 68.4      | 32.2      |

Table 2: Top-1 accuracy [%] obtained by individual methods or combination on UCF101 and HMDB51. STT represent for Spatio-Temporal Transformation and IM for Intra-Video Mixup.

3.4 Discussion

In summary, the proposed STCR is advantageous in the following aspects. i. Spatio-Temporal Transformation is implemented via matrix flip and transpose operations, which costs almost no additional computation. The pseudo codes of Intra-Video Mixup and Spatio-Temporal Transofrmation are presented in Supplementary Section 1. ii. The intuition behind Spatio-Temporal Transformation attributes to the transformation-inverse invariance, i.e., the high-level feature maps of the transformed video after inverse transformation need to be consistent with the feature maps of the original video. Experimental results verify that Spatio-Temporal Transformation can result in clear performance improvement and high-level feature maps become transformation-consistent as illustrated in Section 4.4. iii. For Intra-Video Mixup, consistence of such augmentation can suppress static visual features but preserve temporal motion patterns, which are discriminative for action recognition. Please refer to Section 4.5 for detailed experimental analysis.

4 Experiments

4.1 Datasets and Evaluations

4.1.1 Datasets.

In this section we use two well-known datasets for video self-supervised learning, UCF101 and HMDB51.

UCF101 is an action recognition dataset of realistic action videos, collected from YouTube, having 13,320 videos from 101 action categories.

HMDB51 is collected from various sources and contains 6,849 clips divided into 51 action categories.

4.1.2 Evaluations.

We use PyTorch [21] to implement the whole framework. In order to demonstrate the generality of our work, we use C3D [22], R3D [1], R(2+1)D [23] and I3D [24] as baseline. For each model, the consistency regularization is performed at before the global average pooling layer. We provide complete implementation details of each network in Supplementary Section 2. Results of the final model obtained in the two intermediate steps.

Step 1: Self-supervised Learning. We train and test our self-supervised learning method on split 1 of UCF101. The input clip length is 16 frames and the temporal stride is 4 frames so that the adjacent frames have great visual difference. (The chosen of temporal stride is analysed in Supplementary Section 4.) Specifically, for each clip, we randomly sample 16 frames with interval as 4, and spatially resize the frames as 112 × 112 pixels. We start from learning rate of 0.01, and assign a weight decay of 5e-4. The total epochs is 50 and the learning rate goes down to 1/10 every 10 epochs. H is implement via non-linear ReLU activation followed by FC layer. In all experiments, we set γ to 1e-1 and α as 1 default.

Step 2: Fine-tuning the model. Once we finish the pretraining stage, we use our learned parameters to initialize the 3D CNNs for action recognition, while the last fully connected layer is initialized randomly. During the finetuning and testing, we follow the same protocol in [8] to provide a fair comparison. We apply random spatial cropping and flip
Table 3: Top-1 accuracy [%] obtained by different backbones equipped with STCR.

| Method          | UCF101(%) | HMDB51(%) |
|-----------------|-----------|-----------|
| C3D(random)     | 60.4      | 22.4      |
| C3D + STCR     | 66.4      | 29.2      |
| R3D(random)     | 54.6      | 21.3      |
| R3D + STCR     | 61.2      | 30.4      |
| R(2+1)D(random) | 56.6      | 21.4      |
| R(2+1)D + STCR | 70.5      | 31.9      |
| I3D(random)     | 60.3      | 24.2      |
| I3D + STCR     | 68.4      | 32.2      |

Horizontal to perform data augmentation. We start from a learning rate of 0.05, and assign a weight decay of 5e-4. The total epochs is 45 and the learning rate goes down to 1/10 every 10 epochs.

As our method is generality and can be easily extended to other video understanding task, we also present the experiment of Video Clip Retrieval task in Supplementary Section 6.

4.2 Ablation Analysis

In this section, we give detail ablation study on split 1 of UCF101 and HMDB51. For each experiment, we follow the two steps evaluation on Section 4.1 and we report Top-1 accuracy (%). All methods use I3D as baseline.

Comparison against Variants of Mixup. In this experiment, we point out the merit of using different mixup-based methods under configurations: (a). Maps identical spatial white Gaussian Noise to each frame (Gaussian Noise). (b). Mixes two videos by interpolating the image frame-wise (Video Mixup). (c). Replacing each frame’s one random region with a patch from another frame (Video CutMix). (d). Random select one frame from another video, and mixes each frame with this frame (Inter-Video Mixup). (e). Random select one frame from itself, and mixes each frame with this frame (Intra-Video Mixup).

The result is shown in Table 1. Without available label, Video Mixup and Video CutMix perform worse than the baseline, which demonstrates the importance of keeping semantic consistency. Since the Inter- and Intra- Video Mixup generate semantic-preservation videos, we observe that these two methods are better suited for modeling actions than Gaussion Noise. We also observe that Intra-Video Mixup leads to 2.2% relative gain when compared with Inter-Video Mixup. Notice that the only difference between them is the former selects fixed frame in the same video, we conclude that suppress static image feature is essential for video representation when the size of the dataset is limited.

Ablation Study. In this experiment, we evaluate the effectiveness of each module in STCR independently at first, and then we combine them together. The result is reported in Table 2 and we can make two observations. i. Each of two modules leads to improved accuracy when using both UCF101 and HMDB51 as benchmarks, which indicates these modules have succeeded in learning temporal abstractions. ii. These two modules can be combined to achieve better results (30% higher than train from scratch in HMDB51). More results about atom operation in Spatio-Temporal Transformation are given in Supplementary Section 4.

The influence of backbone. We use 4 types of alterations with varying backbone to test our method: (a). C3D, (b). R3D, (c). R(2+1)D, (d). I3D. The results of this controlled experiment are shown in Table 3. We observe that STCR leads to improved accuracy when using all backbones. As the only change between these models is the usage of STCR, we deduce that the STCR framework has succeeded in learning semantic feature and our method has good generality. We also observe that I3D and R(2+1)D are more competitive than C3D and R3D.

4.3 Experiments on Benchmarks

In this experiment, we compare with state-of-the-art self-supervised learning methods in the video domain. To get the final action recognition result for a video, 10 clips are sampled form the video to get clip predictions, and then averaged to obtain the video prediction. And the other settings were the same as Section 4.1.2. For a fair comparison, all methods use C3D as backbone. As our STCR is a general framework and can be suitable for any self-supervised learning method, except only using STCR as a supervisory, we also combine STCR with [25] and [8] and serve as regularization.

We report the average classification accuracy over 3 splits and compares with other existing self-supervised methods in Table 4. We also show the accuracy from finetuned models which are pretrained on larger supervised datasets such as ImageNet and Kinetics. We can make several observations: i. Compared to train from scratch, our network achieves
| Method                        | UCF101(%) | HMDB51(%) |
|-------------------------------|-----------|-----------|
| Shuffle & Learn [25] [ECCV, 2016] | 50.2      | 18.1      |
| VGAN [26] [NeulPS, 2016]    | 52.1      | -         |
| OPN [27] [ICCV, 2017]       | 56.3      | 22.1      |
| Geometry [28] [CVPR, 2018]  | 55.1      | 23.3      |
| ST Puzzles [12] [AAAI, 2019] | 60.6      | 28.3      |
| Clip Order [8] [CVPR, 2019] | 65.6      | 28.4      |
| Scratch                      | 60.5      | 21.2      |
| ImageNet                     | 67.1      | 28.5      |
| STCR                         | 64.2      | 30.5      |
| STCR (64f)                   | 71.2      | 38.4      |
| Shuffle & Learn [25]+STCR    | 67.3      | 33.4      |
| Clip Order [8]+STCR          | 70.4      | 34.8      |
| Kinetics                     | 96.8      | 74.5      |

Table 4: Comparing our STCR to previous methods in the literature on UCF101 and HMDB51. All methods use the same standard C3D architecture and the accuracies are averaged over three splits. Here STCR (64f) means we finetune STCR with 64 frame input, while the others are 16.

**Figure 4:** The network becomes more transformation consistency via Spatio-Temporal Transformation. These types of transformation correspond to Figure 3.

50% improvement over Scratch and even higher than ImageNet pretrained model in HMDB51. ii. Our STCR leads to significantly improvement with more frames input. The analysis of video clip length is given in Supplementary Section 5. iii. Our network not only achieves prominent performance but also combines well with the others methods, which demonstrates the generality of our method.

### 4.4 Visualization of Spatio-Temporal Transformation

In this experiment, we compare a I3D baseline train from scratch against self-supervised pretrain. And we train 2 baselines with different configurations of pretrain: (a). Train I3D on split 1 of HMDB51 from random initialization with Xavier [29]. (b). First perform self-supervised pretrain with Temporal Augment and then finetune on split 1 of HMDB51.

After finish training, some feature maps generated by these two baselines are randomly selected and visualized. More specifically, we select several samples and random crop a clip with shape $R^{3 \times 64 \times 224 \times 224}$ for each sample. 64 is the number of frames, 3 is the channel and 224 is the width or height. For each sample, $L$ kinds (16 in this paper) Spatio-Temporal Transformations are performed. Then these samples are fed into the I3D. When they feedforward into
the layer $\text{Mixed}_5c$, the high-level feature map is $\mathbb{R}^{1024 \times 8 \times 7 \times 7}$. For these high-level feature maps, we first perform inverse transformation, and then spatial global max pooling is performed first and average pooling along with all channels is followed. So that each transform sample is encoded into a description vector with shape 8. We further stacking these description vectors horizontally as video-level representation, so that the overall matrix is $16 \times 8$.

The result of this experiment is shown in Figure 4. The only difference between the feature from the left half ($c \in [1, 8]$) and the right half ($c + 8$) are with or without adopt temporal flip in Temporal Transformation. It is worth noting that the rotation invariance is barely encoded into the video-level representation under our STCR framework. As shown in Figure 4 the feature maps are various in the same red boxes. However, if the Spatio–Temporal Transformation plays a role as consistency constraint in STCR, then at least the feature map ($c$) from the left half of matrix should keep “consistent” with the right one ($c + 8$). Compared the green boxes in Figure 4, it indicated that the features using Spatio-Temporal Transformation (third row) are more transformation “consistent” than the feature without self-supervised pre-train (second row).

### 4.5 Insight Analysis of Intra-Video Mixup

Besides the results of classification accuracy, this subsection further investigate how Intra-Video Mixup can boost the performance by visualizing representative videos and analyzing performance statistics of different categories.

**Heatmap Visualization.** Figure 5 visualizes the heatmaps of some samples in HMDB51 before and after self-supervised train, using I3D as baseline. Specially, we select some representative samples with significant movement information and then each sample is encoded into $\mathbb{R}^{1024 \times 8 \times 7 \times 7}$ as in Section 4.4. For each channel we perform global max pooling along temporal dimension and enlarge this feature into input size, and then we average the feature map over all channels. In Figure 5, the second row (random initialization with Xavier [29]) and the third row (self-supervised via Intra-Video Mixup) show different heatmaps, which can observe that the network focus more on motion area after self-supervised pretrain.

**Category statistics.** Furthermore, in order to assess the relative performance of Intra-Video Mixup, we make a comparison between scratch and pre-train with Intra-Video Mixup. The result are shown in Figure 6, in which Intra-
Video Mixup excels in temporal-related action categories. The temporal-related action refers to the actions fully relying on motion information and can’t be distinguished in one or a few frames. For example, the HMDB51 dataset has many action categories contain ball, like “kick_ball”, “shoot_ball” and “dribble”. Among these ball-related actions, the model need to focus on motion pattern rater than spatial details to distinguish the specific class (“kick_ball”) from the others (“shoot_ball” and “dribble”). In contrast, Scratch excels in the cases where the action is spatial-related. For example, “shoot_bow” and “ride_bike” can be distinguish in a frame with “bow” and “bike”. It makes sense when considering the Intra-Video Mixup as a “copy” of static image and the “bow” or “bike” might be viewed as noise. The above observations indicated that equipping Intra-Video Mixup is able to learn more temporal abstractions and suppress static image features, which is crucial for temporal-related actions.

We further show the t-SNE visualization result of Intra-Video Mixup in Figure 7. What is obvious is that after the self-supervised learning with Intra-Video Mixup, these samples in embedding space become more diversity (first row). We also observe that Intra-Video Mixup has better “clusters” (red and green box) as we fine-tune on downstream action recognition task.

5 Conclusion

In this paper, we propose a novel Spatio-Temporal Consistency Regularization (STCR) method for self-supervised learning. The proposed method minimizes the variations in different passes of a sample through the network caused by Spatio-Temporal Transformation and Intra-Video Mixup. The proposed method is evaluated by using different CNN backbones on two benchmark datasets. Experimental results show that the proposed STCR outperforms existing methods for action recognition without labelled data for pretraining.

Our future work will study how to make use of other advanced consistency learning methods in the self-supervised setting. On the other hand, besides action recognition, we will further develop self-supervised learning method based on the proposed STCR for other video applications like spatio-temporal action localization.

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Figure 7: The visualization of t-SNE (Intra-video Mixup vs. Scratch). We random select 10 classes from HMDB51. The feature in embedding space become more diversity with Intra-Video Mixup, which suggests that more easily separable features are learned.

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