Few-shot Action Recognition via Improved Attention with Self-supervision

Hongguang Zhang\(^{1,2,3,*}\)  Li Zhang\(^2\)  Xiaojuan Qi\(^2\)  Hongdong Li\(^{1,4}\)  Philip H. S. Torr\(^2\)  Piotr Koniusz\(^{3,1}\)

\(^1\)Australian National University,  \(^2\)University of Oxford  \(^3\)Data61/CSIRO,  \(^4\)Australian Centre for Robotic Vision

firstname.lastname@{anu.edu.au\(^1\), eng.ox.ac.uk\(^2\), data61.csiro.au\(^3\)}

Abstract

Most existing few-shot learning methods in computer vision focus on class recognition given a few of still images as the input. In contrast, this paper tackles a more challenging task of few-shot action-recognition from video clips. We propose a simple framework which is both flexible and easy to implement. Our approach exploits joint spatial and temporal attention mechanisms in conjunction with self-supervised representation learning on videos. This design encourages the model to discover and encode spatial and temporal attention hotspots important during the similarity learning between dynamic video sequences for which locations of discriminative patterns vary in the spatio-temporal sense. Our method compares favorably with several state-of-the-art baselines on HMDB51, miniMIT and UCF101 datasets, demonstrating its superior performance.

1. Introduction

Learning new object classes from few training samples remains an open challenge in computer vision. Recently, a significant progress has been made regarding robust meta-learning strategies \([9, 24, 2]\), robust feature representations and relation descriptors \([32, 35, 42, 38]\), and out-of-class hallucination strategies for insufficient training samples \([16, 43]\). The ultimate goal of few-shot learning is to obtain neural network architectures which can be trained effectively without the need of large scale datasets.

While existing few-shot learning approaches focus on the image-level recognition, very few papers address video-based few-shot learning. As annotating large video datasets is prohibitive, this makes the problem we study particularly useful. For example, so far the largest action recognition dataset, namely Kinetics, consists of 300,000 video clips, each clip contains hundreds of frames, thus actual frame counts exceed the large-scale image classification datasets such as ImageNet and Places205. Yet, the state-of-the-art performance of action recognition is far from satisfactory.

There exist (though very limited) works of few-shot learning for action recognition \([27, 40, 15, 44]\). Most of them focus on the aspect of network design, but without in-depth analysis of various aspects of the specific video domain. Two key aspects are important in few-shot action recognition: i) how to temporally and spatially localize actions of interest in a video with limited number of training samples to effectively suppress the negative influence of temporal and spatial background noises and improve the classification accuracy. ii) how to alleviate the domain shift and overcome overfitting when only a few samples are available for novel classes.

To address these two problems, we propose an improved self-supervised attention mechanism for few-shot action recognition, which simultaneously uses attention modules to localize the actions to improve the accuracy, and feeds numbers of augmented clips into the network with self-supervised loss to enrich training data patterns and improve...
robustness of model. Figure 1 illustrates our idea. Firstly, we impose spatial and temporal attention mechanisms in feature space to detect the frames of interest and regions of interest for action relation learning, thus highlighting the key information and discarding noisy/uninformative background information. Secondly, we apply extensively augmentations on action clips and train a self-supervised discriminator to recognize the augmentation patterns. By providing plentiful patterns of action videos to the network, we can effectively improve the robustness of our few-shot model and reduce its uncertainty.

Furthermore, we apply self-supervision to encourage the attention maps to be robust and consistent in the sense that a robust attention mechanism should be invariant to both temporal and spatial augmentations so that the important spatial/temporal regions matching between augmented and original video pairs could be consistently identified by the attention mechanism irrespective of their actual spatial/temporal locations. However, using a vanilla attention mechanisms without any designated loss cannot guarantee this important property. Therefore, we propose to use self-supervision, where various augmentations are introduced with the goal of attention identifying regions of interest in both augmented and the original clips, while the loss is tasked with unrolling the augmentation itself and minimising the discrepancy between the attention maps.

Our contributions are as follows:

i. We propose an effective and novel pipeline for few-shot action recognition equipped with temporal and spatial attention modules which localize actions and remove suppress an uninformative/noisy background information.

ii. We propose to use temporal and spatial self-supervision for the few-shot action recognition e. g., rotation, spatial and temporal jigsaws, with the goal of improving the model robustness and reduction of overfitting.

iii. We are the first to propose the improved self-supervised attention mechanism via the alignment of action localizing proposals from original and augmented videos with the goal of producing augmentations invariant to location of discriminative patterns.

To the best of our knowledge, this is the first work which incorporates self-supervision into few-shot action recognition, and also the first attempt to use self-supervised attention to produce augmentation-invariant attention maps. Our extensive evaluations demonstrate the effectiveness of the proposed method for few-shot action recognition.

2. Related work

In what follows, we describe recent zero-, one- and few-shot learning algorithms followed by a short discussion on self-supervised learning and second-order pooling approaches.

One- and few-shot learning has been widely studied in both classic [26, 25, 8, 3, 6] and deep learning scenarios [18, 37, 32, 9, 32, 35].

Early works [6, 23] propose one-shot learning methods motivated by the human ability to learn new concepts from very few samples. These two papers employ a generative model with an iterative inference for transfer.

Siamese Network [18] presents a two-streams convolutional neural network approach which generates image descriptors and learns the similarity between them. Matching Network [37] is the first work proposing support-query set and L-way Z-shot learning protocols. It learns to simulate the relations between testing and support images, thus casting the one-shot learning problem as set-to-set learning. Prototypical Networks [32] learns a model that computes distances between a datapoint and prototype representations of each class. Model-Agnostic Meta-Learning (MAML) [9] is trained on a variety of different learning tasks. Relation Net [35] is an effective end-to-end network for learning the relationship between testing and support images. Conceptually, this model is similar to Matching Network [37]. However, Relation Net leverages an additional deep neural network to learn similarity on top of the image descriptor generating network. Then, the similarity network generates so-called relation scores. SalNet [43] proposes an efficient saliency-guided end-to-end sample hallucination strategy to generate richer representations via pairing foregrounds with different backgrounds. Graph Neural Networks (GNN) have also been applied to few-shot learning [11, 17, 13], which demonstrate promising results.

Low-shot action recognition has been investigated in some recent works [27, 15, 40, 44]. Approach [27] proposes a generative framework for zero- and few-shot action recognition by modeling each action class with a probability distribution. Approach [15] leverages neural graph matching to learn/recognize a previous unseen 3D action class with few samples. Approach [40] proposes a dilated network to simultaneously capture local and long-term spatial temporal information for few-shot action recognition. Approach [44] proposes a so-called compound memory network under the key-value memory network paradigm for few-shot video classification.

Despite there exist several methods for few-shot action recognition, each method uses different datasets/evaluation protocols, which makes it hard to produce fair comparisons. Zero-shot learning can be implemented within the similarity learning frameworks which follow [18, 37, 32, 35]. Below we summarize popular zero-shot learning methods. Methods such as Attribute Label Embedding (ALE) [1] use attribute vectors as label embedding and an objective inspired by a structured WSABIE ranking method, which as-
Figure 2. Our few-shot Action Relation Network (ARN) pipeline includes three modules: feature encoder composed by 4-layer 3D convolution blocks, relation network composed by 2D convolution blocks, and a temporal and spatial attention module to refine the 3D action descriptors. We apply second-order pooling over intermediate 3D convolutional features to obtain the Second-order Pooling Matrix (SPM) as the action descriptor, then the relation network learns to capture the relations between support-query action SPM pairs. The extra branch in the bottom of the pipeline connected with blue dashline is the self-supervised learning module, an auxiliary task that regularizes the few-shot learning pipeline. We apply different types of augmentation to the original clips, and we employ the discriminator to recognize how they are augmented.

signs more importance to the top of the ranking list. Zero-shot Kernel Learning (ZSKL) [41] proposes a non-linear kernel method which realizes the compatibility function. The weak incoherence constraint is applied in this model to make the columns of projection matrix incoherent. Feature Generating Networks [39] use GANs to generate additional training feature vectors for unobserved classes.

Self-supervised learning is a learning strategy which leverages easily obtainable labels from trivial tasks such as rotations, patch permutations etc., with the goal of introducing an auxiliary task alongside the classifier to boost object recognition [5, 4, 14], video representation learning [7, 30, 10], and also few-shot image classification [12, 34].

Approach [14] learns to predict random image rotations, approach [4] predicts the relative pixel position, while approach [5] learns to discriminate a set of surrogate classes. Approach [12, 34] proposes to improve the few-shot performance by predicting image rotations and jigsaw patterns.

Second-order statistics have been used for texture recognition [36, 29] by so-called Region Covariance Descriptors (RCD) and further applied to object recognition [20].

A recent approach [31] extracts feature vectors at two separate locations in feature maps and performs an outer product to form a CNN co-occurrence layer. Higher-order statistics have also been used for fine-grained image classification [21] and for domain adaptation [19].

3. Methodology

3.1. Preliminaries

Below we detail our notations and explain the process of computing second-order representations, which is used to aggregate the 3D convolutional action features.

Notations Let $x \in \mathbb{R}^d$ be a $d$-dimensional feature vector. $\mathcal{I}_N$ stands for the index set $\{1, 2, ..., N\}$. Then we use $X = \uparrow \otimes_r x$ to denote the $r$-mode super-symmetric rank-one tensor $X$ generated by the $r$-th order outer-product of $x$, where the element of $X \in \mathbb{R}^d_{x_r}$ at the $(i_1, i_2, ..., i_r)$-th index is given by $\Pi_{j=1}^r x_{i_j}$. Operator $(:)$ denotes vectorisation of a matrix or tensor. Typically, capitalised boldface symbols such as $\Phi$ denote matrices, lowercase boldface symbols such as $\phi$ denote vectors and regular case such as $\phi_{ij}$, $\phi_j$, $n$ or $Z$ denote scalars, e.g. $\phi_{ij}$ is the $(i, j)$-th coefficient of $\Phi$. Finally, $\delta(x - y) = 1$ if $x = y$ and 0 otherwise.

Second- and high-order tensors Below we show that second- and higher-order tensors emerge from a lineariza-
In what follows, we will use second-order matrices obtained from the above expansion for $r = 2$ built from datapoints $\phi$ and $\phi^*$ which are partially shifted by their means $\mu$ and $\mu^*$ so that $\phi := \phi - \beta \mu$, $\phi^* := \phi^* - \beta \mu^*$, and $0 \leq \beta \leq 1$ to account for so-called negative visual words which are the evidence of lack of a given visual stimulus in an image [21].

We define a feature map $\Psi$ with Power Normalization (PN) operator $\mathcal{G}(X)$:

$$
\Psi(\{\phi_n\}_{n \in \mathcal{N}}) = \mathcal{G}\left(\frac{1}{N} \sum_{n \in \mathcal{N}} \phi_n \phi_n^T\right) = \mathcal{G}\left(\frac{1}{N} \Phi \Phi^T\right).
$$

(2)

In this work, $\mathcal{G}$ is a zero-centered Sigmoid function:

$$
\mathcal{G}(X) = \frac{1 - \exp(\sigma X)}{1 + \exp(\sigma X)},
$$

(3)

where $\sigma$ is the factor to control the slope of PN function, and all operations on the matrix are element-wise.

From Eq. (2), one can see that second-order pooling factors out the spatial and/or temporal mode corresponding to column feature vectors stacked in $\Phi$. Thus, videos of various duration may produce various numbers of feature vectors, which will be pooled into a matrix of a constant size independent of the duration of an action. Thus, second-order pooling lends itself to action recognition e. g., one can use one Relation Network [35] with fixed temporal input size irrespective of the duration of a video.

3.2. Pipelines

Our proposed Action Relation Network (ARN) is shown in Figure 2. Similarly to the widely used Conv-4-64 backbone in few-shot image classification [35, 42, 43], we adopt a 3D Conv-4-64 backbone to extract spatio-temporal features. Having obtained the 3D action features, we apply second-order pooling to obtain the co-occurrences which neglect the temporal and spatial positions but highlight co-occurrences of action patterns for pattern learning. We note that second-order pooling is shift-invariant, that is, it discards the spatio-temporal information and thus it is robust to spatial/temporal misalignment. Subsequently, second-order matrices can be fed into a 2D relation network to capture the relations between pairs of action features.

Let $\mathbf{V}$ denote the video input consisting of ~20 frames, and $\Phi \in \mathbb{R}^{C \times T \times H \times W}$ are the features extracted from $\mathbf{V}$ with $f$:

$$
\Phi = f(\mathbf{V}; \mathcal{F}).
$$

(4)

Then we vectorize $\Phi$ to obtain $\Phi \in \mathbb{R}^{C \times THW}$, and apply power normalized second-order pooling to get the Second-order Pooling Matrix (SPM) representation $\Psi \in \mathbb{R}^{C \times C}$:

$$
\Psi = \mathcal{G}\left(\frac{1}{THW} \Phi \Phi^T\right).
$$

(5)

Once SPMs are computed for the support and the query images $\mathbf{I}_s$ and $\mathbf{I}_q$, they are fed into the relation network to obtain the relation score $R_{sq}$:

$$
R_{sq} = r(\theta(\Psi_s, \Psi_q); \mathcal{R}),
$$

(6)

where $r$ denotes the relation network, $\mathcal{R}$ refers to the parameters of $r$, $\theta$ refers to the operator on features of clip pairs e. g., in this paper it is implemented as concatenation along the the channel dimension (third mode) which yields a 3D tensor feature pair.

The objective function we use is the Mean Square Error (MSE) over support and query pairs:

$$
L = \sum_{s \in S} \sum_{q \in Q} (R_{sq} - \delta(l_s - l_q))^2,
$$

(7)

where $\delta$ equals one if $l_s = l_q$, and $l_s$ and $l_q$ denote the class labels of support and query action clips, respectively.
3.3. Temporal and spatial attentions

Below we describe how we use the attention modules in our pipeline. The network architecture of temporal and spatial attention modules is demonstrated in Figure 3, which consists of three 3D Convolutional Blocks and a Sigmoid output layer. Let $t$ and $s$ denote the temporal and spatial attention modules. Note that the attention is applied before second-order pooling in our pipeline. The temporal attention $T \in \mathbb{R}^{1 \times T \times 1 \times 1}$ and the spatial attention $S \in \mathbb{R}^{1 \times 1 \times H \times W}$ are obtained and used as follows:

$$T = t(\Phi; \mathcal{T}),$$

$$S = s(\Phi; \mathcal{S}),$$

$$\Phi^* = (\alpha_t + T) \cdot (\alpha_s + S) \cdot \Phi,$$

where $\mathcal{T}$ and $\mathcal{S}$ refer to the network parameters of temporal and spatial attention modules respectively, $\alpha_t$ and $\alpha_s$ denote the parameters that control the magnitude of attention vectors, $\Phi^*$ denotes the attentive action features.

Leveraging attention mechanisms is a natural way to highlight spatial regions or frames of interests, and suppress uninformative information in the feature space without the use of extra label information, thus it can improve the performance with very little training overhead. In addition, the ideal localizing attention maps should be invariant to data augmentations e. g., spatial rotation and jigsaw, temporal shuffling, et al, thus assuring the expected key frames and regions are accurately localized for relation learning. However, using attention in the above naive way cannot assure this important property, thus we propose to encourage such a property via self-supervision, which is detailed in the following section.

3.4. Improved self-supervised attention mechanism

Self-supervised Learning (SsL) is known from its ability to co-regularize a network and improve classification results. In contrast to previous papers on self-supervised learning, we propose to impose self-supervision not only the features, but also on the attention maps, to enhance the robustness of attention against extensive augmentations. Combining self-supervision with the attention mechanism in a few-shot learning pipeline is a ‘kill two birds with one stone’ type of design which simultaneously enriches the patterns of training samples and effectively improves the robustness of attentions. In this paper, we investigate three types of temporal and spatial self-supervision mechanism to co-regularize the feature encoder and attention modules.
We first start with self-supervision, which is known as an efficient mechanism co-regularizing the network with an auxiliary task related in some way to the main classification task. Thus, for temporal self-supervision, we augment the clips by shuffling the frame orders, which encourages the network to learn the action consistency by observing numbers of shuffled action clips and distinguishing how they are shuffled. Previous self-supervision works on action recognition tried to shuffle the frames at random, however, it is not a meaningful strategy as randomly shuffling all frames breaks up the original action consistency. Thus, we propose a novel temporal shuffling strategy, namely a temporal jigsaw. For the spatial self-supervision, we apply the standard random rotations and random jigsaw permutations.

Below we demonstrate different types of temporal and spatial self-supervision used in our paper:

- **Temporal jigsaw.** Jigsaw solving is known as a popular self-supervision approach to encourage the network ‘understand’ the region-based shuffle. Thus, we propose to segment frames into non-overlapped blocks along temporal mode with a fixed length, then we reorder the clips by shuffling the temporal blocks (rather than frames). In this way, we break up long temporal patterns unlike to repeat in videos but we preserve shorter discriminative patterns to attain a local action consistency.

- **Spatial jigsaw.** We apply jigsaw on spatial dimensions by firstly segmenting the original frames into four non-overlapped patches, then randomly permuting the location of patches to form a new jigsaw frame.

- **Rotation.** Rotation is the most popular self-supervisory task used in recent works. For our problem at hand, we uniformly rotate all frames of an action clip by a random angle e.g., 90°, 180°, 270°.

Similarly to other works on self-supervised learning, we also employ a pattern discriminator demonstrated in Figure 2 in order to recognize the augmentation labels (keys) e.g., the index of center frame for center shift, applied shuffle patterns, and the angle of rotations. Introducing such auxiliary tasks is the strategy underlying self-supervision which we use in this paper.

Below, we illustrate self-supervision via rotations. Consider the objective function $L_{ssl}$ for self-supervised learning with self-supervision discriminator $d$, where $D$ are parameters of function $d$, we have:

$$
\bar{\Phi}_i = f(\text{rot}(V_i, \theta) ; \mathcal{F} ),
$$

(11)

where $V_i$ is a random sampled action clip, $\theta \in \{0^\circ, 90^\circ, 180^\circ, 270^\circ\}$ refers to a randomly selected rotation angle of a frame, $l_0$ denotes the rotation label for sample $i$, which is set to a value among $\{0, 1, 2, 3\}$ corresponding to the rotation degree in the ascending order.

Combining the original loss function $L$ with such a self-supervision term $L_{ssl}$ results in a self-supervised few-shot action recognition pipeline. However, this objective cannot improve the robustness of attention per se. Let us consider our initial concern stating that the attention mechanism is not robust against data augmentations. As numerous augmentation strategies are introduced in the self-supervision module, one can extract the attention for an augmented action clip, then one can augment the attention on the original datapoint with the same augmentation strategy to render augmentations on such a pair mutually neutral, and finally one can align the two attention maps. Such an approach encourages the attention to be consistent and robust to some action group shift (robustness to the used augmentation strategies).

The improved self-supervised attention mechanism is shown in Figure 4. We simultaneously feed the original data and augmented data into the feature encoder to get the SPM representations, then we leverage the attention modules to obtain the localizing attention maps for both inputs. Then we apply the same augmentation on the attention of original data, and align the augmented attention maps of original data with the attention maps of augmented data via the MSE loss. In this way, we encourage the attention modules to produce consistent localizing attention maps for given data irrespective of the spatial and temporal distributions, thus, the attention maps are robust to the action group shifts.

Consider a rotation-guided self-supervised spatial-attention mechanism to demonstrate how the alignment loss $L_{align}$ works. We have:

$$
\bar{\Phi}_i = f(\text{rot}(V_i, \theta) ; \mathcal{F} ),
$$

(14)

$$
\bar{S}_i = s(\bar{\Phi}_i ; \mathcal{S} ),
$$

(15)

$$
\bar{S}_i = s(\bar{\Phi}_i ; \mathcal{S} ),
$$

(16)

$$
L_{align} = \sum_i \| | \text{rot}(S_i, \theta) - \bar{S}_i | - \lambda \|_F^2.
$$

(17)

where $\lambda$ is the parameter to control how strictly the attention are aligned.

The final objective function for our proposed pipeline is given as:

$$
\min L + \beta L_{ssl} + \gamma L_{align}
$$

(18)

where $\beta$ and $\gamma$ are the hyper-parameters adjusted by cross-validation, $L_{ssl}$ is a chosen type of self-supervision.
4. Experiments

4.1. Experimental setup

Prior few-shot action recognition papers use various evaluation protocols in their works, which makes it difficult if not impossible to conduct a fair comparison. Thus, we hope to standardize few-shot training, validation, and test splits on several classic action recognition benchmarks. Below, we describe our setup and evaluations in detail. To exclude complicated data pre-processing and frame sampling steps typically used in action recognition, we randomly sample 20 frames along temporal mode for each dataset and we normalize them by the mean and std.

**HMDB51** [22], an action recognition dataset, contains 6849 clips divided into 51 action categories, each containing a minimum of 101 clips. 31 actions are selected for training, 10 classes for validation and the left 10 actions for testing.

**Mini Moments in Time (miniMIT)** [28] is a subset of the newly proposed large-scale Moments in Time (MIT) dataset. The mini version contains 200 classes and 550 videos per class. We select 120 classes for training, 40 classes for validation and the left 40 classes for test.

**UCF101** [33] contains realistic action videos collected from Youtube. It has 13320 video clips and 101 action classes. We randomly select 70 action categories for training, 10 classes for validation and 21 for testing.

Training, validation and test splits of three datasets are detailed in our supplementary material. The frames of action clips from all three datasets are resized to $128 \times 128$. All models are trained on the training set. Validation set is only used to search for the optimal hyper-parameters, while the test set is used to evaluate our model.

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### Table 1. Evaluations on HMDB51 datasets (given 5-way acc.).

| Model                  | BackBone   | 1-shot     | 5-shot     |
|------------------------|------------|------------|------------|
| Baseline               | 3D Conv-4-64 | 38.05 \pm 0.89 | 53.15 \pm 0.90 |
| **Temporal and Spatial Attentions** |            |            |            |
| ARN+TA                 | 3D Conv-4-64 | 41.97 \pm 0.97 | **57.67 \pm 0.88** |
| ARN+SA                 | 3D Conv-4-64 | 41.27 \pm 0.98 | 56.12 \pm 0.89 |
| ARN+TA+SA              | 3D Conv-4-64 | **42.41 \pm 0.99** | 56.81 \pm 0.87 |
| **Temporal and Spatial Self-supervisions** |            |            |            |
| ARN+SS(spatial-jigsaw) | 3D Conv-4-64 | **44.19 \pm 0.96** | 58.50 \pm 0.86 |
| ARN+SS( rotation)      | 3D Conv-4-64 | 43.90 \pm 0.92 | 57.20 \pm 0.90 |
| ARN+SS(temporal-jigsaw)| 3D Conv-4-64 | 43.79 \pm 0.96 | 58.13 \pm 0.88 |
| **Self-supervised Attentions** |            |            |            |
| ARN+SsSA(spatial-jigsaw) | 3D Conv-4-64 | 45.15 \pm 0.96 | **60.56 \pm 0.86** |
| ARN+SsSA(rotation)     | 3D Conv-4-64 | **45.52 \pm 0.96** | 58.96 \pm 0.87 |
| ARN+SsTA(temporal-jigsaw) | 3D Conv-4-64 | 45.20 \pm 0.98 | 59.11 \pm 0.86 |

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Figure 5. t-SNE visualization of 1-shot models: (a) 3D SoSN, (b) ARN+TA, (c) ARN+SS(t. jigsaw), (d) ARN+SsTA(t. jigsaw). It can be clearly seen that the feature space is optimized by our propose self-supervised attention.

4.2. Analysis

We equip the Prototypical Net [32], Relation Net [35] and SoSN [42] with 3D convolutional feature encoder as our baselines for comparisons in this paper. Tables 1 and 2 show that 3D SoSN attains the top performance on all evaluation protocols.

**Attention.** Tables 1 and 2 investigate the temporal (TA) and spatial (SA) attention mechanisms on our Action Relation Network (ARN). The temporal attention on the 1-shot and 5-shot protocols improves the accuracy by 1.0\% and 2.5\%, the spatial attention boosts the 1- and 5-shot accuracy by 0.5\% and 1.0\%, respectively.

For the simultaneous spatio-temporal attention (TA+SA),
The figures show that applying the attention alignment outperforms the basic attention with self-supervision ($\gamma = 0$).

the shifted Sigmoid function from Eq. (10) is needed to achieve further improvements. Empirically, we run a cross-validation and set $\alpha_t = 1.0$ and $\alpha_s = 0.5$ for HMDB51, and $\alpha_t = 1.5$ and $\alpha_s = 1.0$ for UCF101. The spatio-temporal attention achieves further improvements for 1-shot learning but not always is helpful on 5-shot learning. For example, it improves the 1-shot accuracy by 0.5% while leads to an 0.8% drop on for the 5-shot protocol on HMDB51.

**Self-supervision.** Three types of self-supervision are evaluated in Tables 1 and 2. Applying self-supervision w.r.t either temporal mode (SsTA) or spatial mode (SsSA) boosts performance for 1-shot and 5-shot learning on HMDB51 between 2.0 and 3.2%, on miniMIT between 1.2 and 4.6% and on UCF101 between 0.6 and 1.4%. However, for UCF101 dataset, two types of self-supervision (spatial jigsaw and rotation) lead to a marginal performance drop on 5-shot learning compared to 3D SoSN [42]. The possible reason that UCF101 is an easy recognition benchmark and the action representations learned with in 5-shot setting are already sufficiently discriminative. As augmentation-based supervision is geared towards datasets containing larger geometric transformations, it may be suboptimal on UCF101.

**Improved self-supervised attention mechanism.** According to our evaluations, using self-supervision to align attention improves the few-shot performance on all protocols. However, it is worth noting that not all self-supervised attention patterns are useful. According to Tables 1 and 2, using temporal-jigsaw to enhance attention can effectively improve the 1-shot performance by 1.5% on HMDB51 and UCF101, and by 1% on miniMIT. We present the training loss-epoch curves of SsTA (t. jigsaw) and validation of $\gamma$ for SsSA(rot.) in Figure 6 on HMDB51 dataset. As can be seen, the improved self-supervised attention mechanism performs better than simply combining self-supervision with attention ($\gamma = 0$). We also investigate ‘apply spatial self-supervision to enhance temporal attention’ and ‘apply temporal self-supervision to enhance spatial attention’ strategies. However, it appears that these cross-pattern alignments have very limited influence on the quality of attention vectors.

| Model                     | miniMIT          | UCF101          |
|---------------------------|------------------|-----------------|
|                           | 1-shot | 5-shot   | 1-shot | 5-shot |
| 3D Prototypical Net [32]  | 33.65 ± 1.01     | 45.11 ± 0.90   | 57.05 ± 1.02 | 78.25 ± 0.73 |
| 3D RelationNet [35]       | 35.71 ± 1.02     | 47.32 ± 0.91   | 58.21 ± 1.02 | 78.35 ± 0.72 |
| 3D SoSN [42]             | 40.83 ± 0.99     | 52.16 ± 0.95   | 62.57 ± 1.03 | 81.51 ± 0.74 |

### Temporal and Spatial Self-Supervisions

| Model                     | miniMIT          | UCF101          |
|---------------------------|------------------|-----------------|
|                           | 1-shot | 5-shot   | 1-shot | 5-shot |
| ARN+TA                   | 41.65 ± 0.97     | 56.75 ± 0.93   | 63.35 ± 1.03 | 80.59 ± 0.77 |
| ARN+SA                   | 41.27 ± 0.98     | 55.69 ± 0.92   | 63.73 ± 1.08 | 82.19 ± 0.70 |
| ARN+TA+SA                | **41.85 ± 0.99** | **56.43 ± 0.87** | **64.48 ± 1.06** | **82.37 ± 0.72** |

### Temporal and Spatial Self-Supervisions

| Model                     | miniMIT          | UCF101          |
|---------------------------|------------------|-----------------|
|                           | 1-shot | 5-shot   | 1-shot | 5-shot |
| ARN+SS(spatial-jigsaw)    | **42.68 ± 0.95** | 54.46 ± 0.88   | 63.75 ± 0.98 | 80.92 ± 0.72 |
| ARN+SS(rotation)           | 42.01 ± 0.94     | **56.83 ± 0.86** | 63.95 ± 1.03 | 81.09 ± 0.76 |
| ARN+SS(temporal-jigsaw)    | 42.45 ± 0.96     | 54.67 ± 0.87   | 63.79 ± 1.02 | **82.14 ± 0.77** |

### Temporal and Spatial Self-Supervisions

| Model                     | miniMIT          | UCF101          |
|---------------------------|------------------|-----------------|
|                           | 1-shot | 5-shot   | 1-shot | 5-shot |
| ARN+SsSA(spatial-jigsaw)  | 42.92 ± 0.95     | 56.21 ± 0.85   | 66.04 ± 1.01 | 82.68 ± 0.72 |
| ARN+SsSA(rotation)         | 43.27 ± 0.97     | 56.71 ± 0.87   | **66.32 ± 0.99** | **83.12 ± 0.70** |
| ARN+SsTA(temporal-jigsaw)  | **43.56 ± 0.96** | **57.35 ± 0.85** | 65.46 ± 1.05 | 82.97 ± 0.71 |

**5. Conclusions**

In this paper, we take a deeper look at the few-shot action recognition task, and propose a novel action relation network with an improved self-supervised attention mechanism to address the related concerns. Our approach encourages the spatio-temporal attention consistency by aligning the attention on variously augmented representations, which helps localize discriminative spatial regions and temporal locations to improve the performance. For the future work, we will investigate new augmentation strategies and attention models. We believe our novel strategy will benefit numerous tasks in computer vision e. g., few-shot action recognition, object detection, segmentation, saliency detection, and semantic segmentation.
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Appendices

A. Evaluation Protocols

Below we demonstrate the detailed train-validation-test splits used in our paper. Though the limited previous works propose some evaluation splits on the classic action recognition datasets, they differs in every paper thus making it impossible to produce fair comparisons with other works. Additionally, some splits e.g., proposed in [27], have no validation set, which makes the results not convincing as the model can be highly overfitted to test set, and has limited generalized capability. Here we want to fix these problems and formally introduce the new splits as the standard benchmarks, which can more accurately demonstrate the models’ performance, and also make it easier to fairly compare with the future few-shot action recognition works.

A.1. HMDB51 [22]

Actions of Train Split (31): brush hairs, catch, chew, clap, climb, climb stairs, dive, draw sword, dribble, drink, fall floor, flic flac, handstand, hug, jump, kiss, pullup, punch, push, ride bike, ride horse, shake hands, shoot bow, situp, stand, sword, sword exercises, throw, turn, walk, wave.

Actions of Validation Split (10): cartwheel, eat, golf, hit, laugh, shoot ball, shoot gun, smile, somersault, swing baseball.

Actions of Validation Split (10): fencing, kick, kick ball, pick, pour, pushup, run, sit, smoke, talk.

A.2. miniMIT [28]

Actions of Train Split (120): arresting, assembling, attacking, baking, barbecuing, barking, bending, bicycling, biting, boating, bouncing, brushing, bulldozing, burning, camping, carrying, celebrating, chopping, clapping, cleaning, clinking, closing, combing, competing, covering, crawling, crying, cutting, descending, destroying, digging, dining, drawing, drenching, drinking, dripping, driving, dropping, drying, dunking, emptying, entering, erupting, falling, filling, flipping, floating, flying, folding, frying, handwriting, hangin, hitting, juggling, kicking, knitting, landing, laughing, leaping, lecturing, lifting, mopping, opening, parading, photographing, picking, placing, pouring, pressing, protesting, pulling, pushing, rafting, raining, reading, removing, repairing, riding, rising, rowing, running, sawing, scratching, sewing, shaking, shaving, shopping, shouting, shredding, singing, skating, sleeping, slicing, sliding, smiling, smoking, snowing, speaking, spraying, spreading, sprinting, stacking, stirring, stitching, stretching, stroking, studying, swimming, swinging, tapping, tattooing, turning, twisting, typing, vacuuming, walking, washing, whistling, wrapping.

Actions of Validation Split (40): ascending, boiling, bubbling, chasing, combusting, constructing, cracking, crashing, crushing, diving, drumming, eating, exercising, gardening, grilling, grooming, hammering, hugging, inflating, licking, painting, peeling, pitching, planting, playing, playing sports, rolling, sanding, shaving, smashing, spinning, steering, surfing, sweeping, tapping, throwing, unloading, watering, waving, wrestling.

Actions of Test Split (40): boxing, car, catching, cheering, chewing, climbing, colliding, cooking, crafting, dancing, feeding, fishing, flooding, frowning, gripping, hiking, howling, jumping, launching, mowing, overloading, pedaling, performing, piloting, playing music, racing, raising, resting, rubbing, sailing, slapping, sneezing, sniffing, splashing, storming, tyng, waking, waxing, welding, yawning.

A.3. UCF101 [33]

Actions of Train Split (70): ApplyEyeMakeUp, Archery, BabyCrawling, BalanceBeam, BandMarching, BaseballPitch, Basketball, BasketballDunk, BenchPress, Biking, Billiards, BlowDryHair, BodyWeightSquats, Bowling, BoxingPunchingBag, BoxingSpeedBag, BreastStroke, BrushingTeeth, CricketBowling, Drumming, Fencing, FieldHockeyPenalty, FrisbeeCatch, FrontCrawl, Haircut, Hammering, HeadMassage, HulaHoop, JavelinThrow, JugglingBalls, JumpingJack, Kayaking, Knitting, LongJump, Lunge, MilitaryParade, Mixing, MoppingFloor, Nunchucks, ParallelBars, PizzaTossing, PlayingCello, PlayingDhol, PlayingFlute, PlayingPiano, PlayingSitar, PlayingTabla, PlayingViolin, PoleVault, Pullups, PushUps, Rafting, RopeClimbing, Rowing, ShavingBeard, Skijet, SoccerJuggling, SoccerPenalty, SumoWrestling, Swing, TableTennisShot, Taichi, ThrowDiscus, TrampolineJumping, Typing, UnevenBars, WalkingWithDog, WallPushups, WritingOnBoard, YoYo.

Actions of Validation Split (10): ApplyLipstick, CricketShot, HammerThrow, HandstandPushups, HighJump, HorseRiding, PlayingDaf, PlayingGuitar, Shotput, SkateBoarding.

Actions of Test Split (21): BlowingCandles, CleanAndJerk, CliffDiving, CuttingInKitchen, Diving, FloorGymnastics, GolfSwing, HandstandWalking, HorseRace, IceDancing, JumpRope, Pomme|eHorse, Punch, RockClimbingIndoor, SalsaSpin, Skiing, SkyDiving, StillRings, Surfing, TennisSwing, VolleyballSpiking.
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