Multi-View Action Recognition using Contrastive Learning

Ketul Shah[1] Anshul Shah[1] Chun Pong Lau[1] Celso M. de Melo[2] Rama Chellappa[1]
[1]Johns Hopkins University [2]DEVCOM Army Research Laboratory
{kshah33, ashah95, clau13, rchella4}@jhu.edu celso.miguel.de.melo@gmail.com

Abstract

In this work, we present a method for RGB-based action recognition using multi-view videos. We present a supervised contrastive learning framework to learn a feature embedding robust to changes in viewpoint, by effectively leveraging multi-view data. We use an improved supervised contrastive loss and augment the positives with those coming from synchronized viewpoints. We also propose a new approach to use classifier probabilities to guide the selection of hard negatives in the contrastive loss, to learn a more discriminative representation. Negative samples from confusing classes based on posterior are weighted higher. We also show that our method leads to better domain generalization compared to the standard supervised training based on synthetic multi-view data. Extensive experiments on real (NTU-60, NTU-120, NUMA) and synthetic (RoCoG) data demonstrate the effectiveness of our approach.

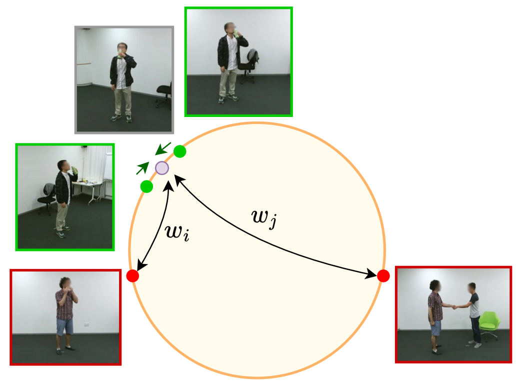


Figure 1: Motivation. In addition to being robust to augmentations and temporal shifts, the feature embeddings of synchronized viewpoints should be close in feature space. Further, hard negatives should be handled differently from easy ones for optimal learning. We realize these objectives using a novel hardness-aware contrastive learning loss.

1. Introduction

Action recognition from videos is an active area of research [55, 70] in computer vision. A lot of work has focused on making better use of spatio-temporal information [54, 19, 4], developing more efficient architectures [18, 36, 62], etc. The hope is to learn models which are robust to novel viewpoints at test time. Much of this recent progress in action recognition is based on datasets where viewpoint information is not explicitly available. Our paper focuses on multi-view action recognition in scenarios where synchronized multi-view videos are available during training. This scenario arises in many practical applications in security, road safety, robotics, sports, etc.

Multi-view action recognition has been extensively studied, the availability of large scale datasets [50, 37] driving recent progress of deep learning-based methods. Approaches based on RGB [57, 11], depth [26], infrared [13], skeleton [39, 8] modalities have been proposed. Recent advancements in multi-view action recognition are heavily focused on skeleton-based action recognition. 2D [71] and 3D [20, 8] skeleton-based methods have achieved state-of-the-art performance on benchmark datasets.

Methods relying on ground truth 2D/3D human pose information often assume access to datasets annotated with pose information, which is not necessarily available in data collected for real life applications. Annotating videos for ground truth pose is very expensive and dataset collectors often rely on specialized hardware (like Kinect) which exploit depth sensors to obtain accurate skeletons. An alternative could be to use estimated pose, but human pose estimation from RGB videos can be challenging, especially in scenarios where activities include human-object interactions, complex scenes with multiple people and heavy occlusion. Moreover, high quality pose estimation methods are slow, as most of these methods rely on object detection as an intermediate step. In most practical settings, multi-view setups have only RGB cameras.

In this paper, we focus on RGB-based multi-view action recognition. Fig. 1 presents an overview of our approach.

https://github.com/kshah33/ViewCon

We use contrastive loss to achieve viewpoint robustness, leveraging videos captured simultaneously from multiple viewpoints. Specifically, we propose an improved version of supervised contrastive loss, and incorporate viewpoint synchronized videos as additional positives.

The quality and number of negatives is known to be important for contrastive learning [24, 49]. It has been shown [49, 47] that use of hard negatives for contrastive loss improves the quality of learned representations. Motivated by these observations in the self-supervised learning setting, we propose a novel approach for using hard negatives with contrastive loss in supervised settings. Our approach enables the classifier to guide the selection of negatives. Intuitively, the classifier gives a high score for confusing classes. This information lets us upweight negatives belonging to those classes for contrastive learning, effectively learning better features. We term the resulting hardness-aware contrastive loss ViewCon.

Extensive experiments on the NTU-RGB+D [50, 37] and NUMA [60] datasets demonstrate that our method can learn discriminative viewpoint-invariant representations, which can be used for transferring to small datasets showing generalization capability. We achieve state-of-the-art results compared to previous RGB-based approaches on these datasets. We also analyze the various design choices for our loss function. We note that it can be difficult to acquire synchronized multi-view videos for arbitrary real world scenarios/applications and there are associated privacy concerns. Synthetic data provides a natural solution to these problems, where it is easy to generate large-scale synchronized multi-view data without any privacy issues. We show that our approach also gives consistent improvements on a synthetic multi-view dataset [14] and that the resulting features generalize better to the real test data.

Our main contributions are summarized below:

- We propose a method for RGB-based action recognition, using contrastive learning to leverage multi-view training videos for achieving robustness to viewpoints.
- We propose a novel way to sample hard negatives for contrastive loss in the supervised setting by re-weighting the negatives using class probabilities. To the best of our knowledge, the use of hard negatives with supervised contrastive learning has not been explored before.
- Our method achieves state-of-the-art results on the popular NTU-60, NTU-120 and NUMA datasets. We also show the effectiveness of our method when using synthetic training data, and in transfer learning setting, validating our method in diverse scenarios.

2. Related Work

Action Recognition. There has been significant progress in action recognition, from traditional methods [55], to the latest advancements using deep learning [70]. Two-stream networks [54] was one of the first works to show effectiveness of using two-stream CNN, for integrating appearance and flow features. I3D [4] introduced the idea of inflating 2D CNN weights learnt from image datasets for effectively training 3D CNNs. S3D [64] replaces spatio-temporal 3D CNN layers by factored spatial and temporal 3D convolutions, and also incorporates feature gating in their architecture. SlowFast networks [19] introduces two pathways, a low frame-rate slow pathway for encoding spatial semantics and a high frame-rate fast pathway to capture motion dynamics. [18, 36, 62] aim to increase efficiency, and transformer-based architectures have recently been proposed [65] for action recognition.

While these methods show impressive performance, they are prone to learn shortcuts and capture biases such as scene, objects, context, viewpoints, etc [61, 35] and hence may not generalize well. [32, 35] provides ways of quantifying these biases for video models. [9] mitigates scene bias by using an adversarial loss for scenes based on gradient reversal, along with a human mask confusion loss. [66, 59] suppresses scene information by performing video transformations in the self-supervised learning setting. All the methods discussed above mainly deal with single-view videos, and do not consider multi-view action recognition.

Multi-View Action Recognition. Large-scale datasets with multiple modalities (RGB, infrared, depth, skeleton, etc) for multi-view action recognition [50, 37, 10] have enabled recent progress in this area. A dominant paradigm among these methods is to learn viewpoint-invariant representations [42, 63, 56, 69, 30, 46]. More recently, [33] uses source view features to predict 3D motion in multiple target views for unsupervised view-invariant feature learning. In a similar spirit, [57] uses cross-view prediction as an auxiliary task for learning RGB-based view-invariant representations. [11] employs a learnable viewpoint-generator based on a neural projection layer along with a contrastive loss. [57, 33, 45] makes use of depth videos for view-invariant learning.

Skeleton-based methods [8, 20, 39, 31, 52, 53, 34, 3, 38, 67] have received a lot of attention due to the availability of accurate 3D skeleton ground truth in the benchmark datasets (all in indoor settings) as they are collected using Kinect. [20] proposes a geometry-aware deep neural network for processing skeleton data, using rigid and non-rigid transformations. [39] uses a disentangled multi-scale aggregation scheme, processed with a unified spatial-temporal graph convolution network. [53] proposes an efficient skeleton-based method by adaptively controlling the number of input joints and the model size based on input. Approaches combining skeleton and appearance modalities [12, 10, 1, 40] have also been studied in literature.

Most of the current state-of-the-art methods use ground truth 3D skeleton information for training and testing. It is difficult to estimate accurate 3D skeleton for videos in-the-wild without access to depth information. Hence, we focus on RGB-based multi-view action recognition.

Contrastive Learning. Contrastive learning has recently become a popular paradigm for learning self-supervised representations, and has enjoyed wide success. [6, 24] have shown superior performance compared to supervised learning methods for image classification. The main idea of contrastive learning is based on the classical noise-contrastive estimation (NCE) [22], with recent methods adapting it to effectively solve the instance classification task. The goal is to learn a discriminative feature space by classifying positives (which are typically defined as data-augmented versions of input) from negatives. In the image domain, [6] studies the effect of data-augmentations for defining positives and introduces the use of a non-linear projection head for learning better representations. [24] enables the use of more negatives by maintaining a queue. The idea has been extended to video domain [44, 17], where [44] uses temporally distant clips from a given video with spatial augmentations as positives. Negatives are chosen from other videos. [17] additionally incorporates temporally shuffled negatives from the same video.

There has been work to adapt contrastive loss for supervised learning [29, 48, 5]. [29] extends the contrastive loss to leverage label information, and suggests ways for incorporating multiple positives in the contrastive loss. Supervised contrastive loss has been applied for tasks such as domain adaptation [48], continual learning [5], etc.

Hard Negatives for Contrastive Learning. The quality of representations learned using contrastive loss is dependent on the amount and quality of negative samples used. Recently, [28, 49, 47] have proposed ways to choose and include hard negatives in the contrastive loss for self-supervised setting. [28] uses mixup to generate hard negatives by combining highest similarity samples in the queue with each other, and with the anchor. [49] selects hard negatives as a sparse set of support vectors and contrastiveness is enforced by maximizing the margin between positives and negatives. [47] proposes a method to select hard negatives based on the similarity of negatives to the anchor.

We propose to leverage hard negatives for the supervised contrastive learning setting, which to the best of our knowledge has not been explored.

3. Method

In this section, we first discuss the problem setup before presenting our approach dubbed ViewCon.

Problem Formulation. Let us denote the dataset $\mathcal{D}$ as $\{(x_i^1, x_i^2, ..., x_i^V), y_i\}_{i=1}^N$, where each activity instance i consists of synchronised videos $(x_i^1, x_i^2, ..., x_i^V)$ captured from V viewpoints, with class label y_i where $y_i \in \{1, ..., C\}$. C denotes the total number of classes. The dataset consists of a total of $N \times V$ videos, with N activity instances, each captured from V viewpoints.

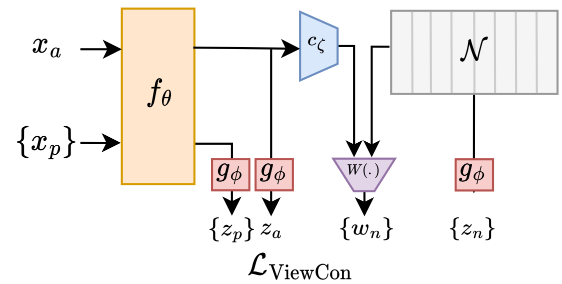


Figure 2: Overall pipeline. We first extract features for the anchor x_a and positives $\{x_p\}$. The classifier scores of the anchor are used to generate weights for negatives $\mathcal{N}$ using the function $W(.)$. The weights along with the projected features (obtained using g_ϕ) for the anchor, positives and negatives are used to compute the ViewCon loss.

The goal is to learn a function f_θ which maps a video clip to its representation, such that the representation is robust to changes in viewpoint, while also being discriminative of action classes. We use contrastive learning to guide feature embeddings of different viewpoints of the same activity instance nearby in the feature space, close to same class features. Contrastive learning methods usually devise different ways of defining positives (data augmentations, sampling at different frame rate, etc), such that the semantic content in the data is preserved. [6, 24] use scaling, color jittering, blurring, etc as augmentations, and [44, 23] use optical flow, varying frame rate clips, etc as positives to learn features robust to these changes. In our work, we seek view invariance in addition to robustness from various data augmentations. To do so, we use features of different viewpoints of the same activity instance as positives, to pull them closer. We employ an improved version of the supervised contrastive loss to realize this. We also propose a novel method to make effective use of hard negative samples in the contrastive loss, by leveraging classifier probabilities. Finally, we discuss different practical considerations involved in using these successfully. The overall pipeline is shown in Fig. 2. Next, we describe each part of our method in detail.

View Contrastive Learning Contrastive learning-based methods have shown great success in self-supervised representation learning [6, 24, 25, 7, 23], as well as supervised representation learning [29]. Our method is based on the MoCo v2 [7] framework, which we briefly describe next.

Given an input video clip, an anchor (query) and a positive (key) sample is generated. The anchor sample is passed through an encoder f_θ to obtain anchor features, and a momentum updated version of the encoder is used to obtain positive features. A projection head g_ϕ is used to project these features to a lower dimensional space, where the contrastive loss is computed. A queue stores positive features from previous batches which are used as negatives in the contrastive loss. For this task of instance discrimination, the InfoNCE loss [6] is used for training encoder and projection head.

[29] studies ways to extend the InfoNCE loss to supervised setting where we have multiple positives, and no false negatives. The supervised contrastive loss proposed by [29] is given in Eq. 1.

$$\mathcal{L}_{\text{SupCon}} = \frac{1}{|\mathcal{P}_i|} \sum_{p \in \mathcal{P}_i} \mathcal{L}(i,p) \tag{1}$$

$$\mathcal{L}(i,p) = -\log \frac{\exp(z_i \cdot z_p/\tau)}{\sum\limits_{p \in \mathcal{P}_i} \exp(z_i \cdot z_p/\tau) + \sum\limits_{n \in \mathcal{N}_i} \exp(z_i \cdot z_n/\tau)} \tag{2}$$

Here, for an anchor video clip x_i belonging to class y_i, the positive set $\mathcal{P}_i$ is made of data-augmented clips from other videos with the same label, in addition to augmented anchor clip. $\mathcal{N}_i$ is the set of negatives, which contains clips from other classes. $z_i \cdot z_j$ denotes the cosine similarity between normalized features of clips x_i and x_j. τ is the temperature parameter.

We improve the loss in Eq. 2 as discussed below and use the updated loss in our method. Note that Eq. 2 can be viewed as performing $|\mathcal{P}_i| + |\mathcal{N}_i|$ way classification, for classifying the positive sample in the numerator, from all the samples included in the denominator. We argue this is not ideal, since it tries to discriminate one positive from other *positives*, and hence we propose to remove other positives from the denominator (as in Eq. 4). This effectively leads to discrimination of the current positive only from other negatives.

Moreover, our problem formulation allows us to use synchronized viewpoints as positives, which helps us achieve robustness to viewpoints. More specifically, given an anchor video clip x_i from class y_i, the positive set $\mathcal{P}_i$ is constructed with three types of positives: 1) augmented clip from the same video, 2) clips from videos of other viewpoints of this instance, and 3) clips from other instances of the same class. The negative set $\mathcal{N}_i$ consists of clips from videos belonging to other classes. Intuitively, construction of our positive and negative set enforces features from different viewpoints of the same activity instance to be pulled together while being pushed away from features of other activity classes. Next, we describe our approach for sampling hard negatives.

Hard Negative Sample Re-weighting. Hard negative sampling for self-supervised contrastive learning [49, 47, 28] has been proven effective in learning better representations.

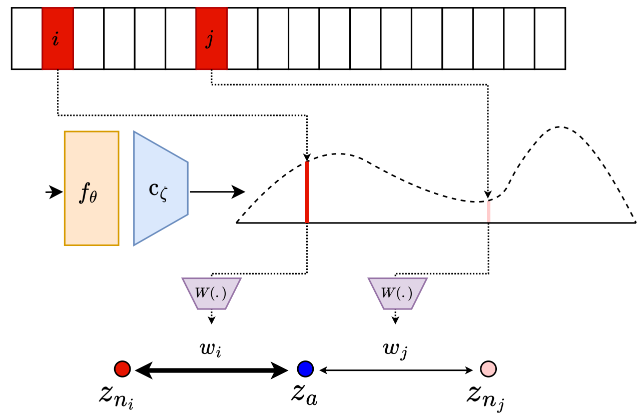


Figure 3: Generating negative weights. Consider negative i belonging to class y_i. The classifier score $p(y|x_a)$ is indexed at y_i to generate weights w_i which is used to weigh the exponential similarity between anchor and the negative in our contrastive learning framework. Our approach effectively generates higher weights for classes confusing to the anchor (hard negatives).

In our supervised contrastive setting, we propose to leverage the classifier probabilities for selecting and re-weighting hard negative samples in the contrastive loss.

Specifically, given an anchor clip x, its features ($h = f_\theta(x)$) are passed through the classifier c_ζ to obtain a probability distribution $p(y|x)$ over all classes, where $p(y|x) \in \mathbb{R}^C$. The probability of classifying input clip x to class y_j is given by $p(y_j|x)$. This is used to determine the hardness of class y_j for anchor x. To see this, note that classes more similar to anchor class are harder to discriminate (and receive higher probability) than classes which are very distinct from the anchor class (which receive low probability). For example, *typing on keyboard* is much more similar to *writing on paper* than *clapping*. As shown in Fig. 3, a negative sample x_n belonging to class y_n in the contrastive loss is re-weighted using w_n, which is proportional to $p(y_n|x)$ (the probability of anchor clip being classified to class y_n). The updated hardness-aware view contrastive loss (dubbed ViewCon) is given in Eq. 3 below:

$$\mathcal{L}_{\text{ViewCon}} = \frac{1}{|\mathcal{P}_i|} \sum_{p \in \mathcal{P}_i} \mathcal{L}_1(i,p) \tag{3}$$

$$\mathcal{L}_1(i,p) = -\log \frac{\exp(z_i \cdot z_p/\tau)}{\exp(z_i \cdot z_p/\tau) + \sum\limits_{n \in \mathcal{N}_i} w_n \exp(z_i \cdot z_n/\tau)} \tag{4}$$

Here, $w_n \propto p(y_n|x_i)$. Negative classes similar to anchor x_i class will have higher $p(y_n|x_i)$ and will be weighted higher.

We now explain how we obtain the final weights $\{w_n\}_{n \in \mathcal{N}_i}$ for an anchor x_i, given the classifier probabilities $p(y|x_i)$ and the labels of negatives $\mathcal{N}_i$. First, we assign the weight w_n for each negative sample x_n from class y_n to $p(y_n|x_i)$. Note that these weights lie in $[0, 1]$, and hence only allow decreasing the effective similarity (pushing farther in feature space). To see this, recollect that term $s_{i,n} = z_i \cdot z_n$ calculates the similarity between L2-normalized features of the anchor z_i and those of a negative sample z_n. Our approach weights this exponential similarity by w_n as in Eq. 4. This reweighting can be seen as effectively modifying the original similarity with $s_{i,n}^{new} = \tau \log w_n + s_{i,n}$. It can be seen that weights less than one reduces effective similarity. Next, we normalize the weights by the average weight, *i.e.* $w_n \leftarrow w_n/\text{mean}(w_n)$, now allowing the weights to take values greater than one. We clamp the minimum value of weights w_n to 1, thus only allowing increasing effective similarity.

We also note that the weights resulting from classifier probabilities can be highly skewed if the classifier gives overconfident predictions. Our approach relies on the fact that there are multiple peaks in the probability distribution which helps reweight the negatives. Note that overconfident predictions would likely lead to a single dominant peak which will lead to very small weights. To correct this, we use label smoothing for regularization and it helps in getting better calibrated classifier predictions [41], resulting in more useful weights.

Action Classifier. In the supervised contrastive learning setting, it is a common practice [29] to pre-train using the contrastive loss and train the classifier on top in a separate stage while also fine-tuning the backbone. We instead train the classifier simultaneously, and propose to use the output probabilities of the classifier to guide sampling of hard negatives for contrastive loss as described above. The classifier is trained using the cross-entropy loss L_{CE}. This loss is only used to train the classifier and the gradients are not backpropagated to the encoder. We use label smoothing for training the classifier in all our experiments as it reduces overconfident predictions and helps provide more calibrated classifier probabilities, as shown in [41].

Algorithm 1 ViewCon loss computation

Input: anchor x_a, positives $\{x_p\}$, negative features $\mathcal{N}$, feature extractor f_θ, projection MLP g_ϕ, classifier c_ζ, temperature τ
Output: loss,
  # extract features h and classifier output
  $h_a, \{h_p\}$ = `extract_features(`$x_a, \{x_p\}, f_\theta$`)`
  c_a = `classify(`h_a, c_ζ`)`
  # project and L2 normalize
  $z_a, \{z_p\}$ = `projector(`$h_a, \{h_p\}, g_\phi$`)`

  # query GT class for all negatives
  $\{y_n\}$:= `get_class(`$\mathcal{N}$`)`
  # index prob for GT class of each negative
  $\mathcal{W} := \{$`index(`c_a, y_n`)`$\}_{n=1}^{|\mathcal{N}|}$
  # normalize and clamp minimum to 1
  $\{w_n\}$ = `clamp(`$|\mathcal{N}|\frac{\mathcal{W}_n}{\sum \mathcal{W}_n}$`, 1,` ∞`)`

  # calculate ViewCon loss (Eq. 3)
  $\text{loss}_{\text{ViewCon}} = \mathcal{L}_{\text{ViewCon}}(z_a, \{z_p\}, \{z_n\}, \{w_n\}, \tau)$

4. Experiments

In this section, we present experimental results to show the effectiveness of the proposed approach.

4.1. Datasets

NTU-RGB+D 60. NTU-60 [50] is a large-scale multi-view action recognition dataset containing 56880 videos from 60 action classes, captured from 40 subjects, using Kinect v2. Each activity instance is captured at the same time from three different viewpoints. We evaluate our method on the two standard benchmarks as provided in [50]: (1) Cross-Subject (xsub) and (2) Cross-View (xview). For the cross-subject benchmark, the 40 subjects are split into two sets, for training and testing, with 20 subjects each. For the cross-view setting, videos from cameras 2 and 3 are used for training, and videos from camera 1 are used for testing.

NTU-RGB+D 120. NTU-120 [37] is the extended version of NTU-60 dataset, consisting of 114480 videos from 120 action categories. We evaluate on the two standard protocols as in [37]: (1) Cross-Subject (xsub) and (2) Cross-Setup (xset). The cross-subject setting splits the subjects into training and testing subjects, whereas the cross-setup setting divides the data into training and testing based on the setup ID.

Northwestern-UCLA Multiview Action. NUMA [60] is a smaller dataset consisting of 1493 videos from ten action classes. Each action is performed by ten actors and is captured from three viewpoints. The dataset provides RGB, depth, and skeleton modalities. We use this dataset for transfer learning setting and only use RGB frames for our experiments.

Robot Control Gestures. RoCoG [14] is a gesture recognition dataset for studying the usefulness of synthetic data. It consists of synthetic and real videos from seven gestures captured from multiple viewpoints. The real data includes videos from fourteen subjects, while synthetic data is rendered with varying parameters such as character, environment, camera angle, etc. We use the training and testing splits provided in [14].

4.2. Implementation details

We choose S3D [64] as our encoder f_θ for all our experiments. A 2-layer MLP with ReLU non-linearity is used as the projection head g_ϕ, a common practice as in [6, 7]. The action classifier is a single linear layer with batch norm, whose inputs are L2-normalized. The encoder takes clips of 32 RGB frames as inputs with a skip rate of 2, which are sampled starting from a random time from the input video. We apply the following clip-consistent data augmentations: random crop, horizontal flip, gaussian blur, and color jitter. We use a queue size of 2048 to cache negative features, and use momentum of 0.999 for the momentum updated encoder and projection head. Label smoothing of 0.6 is used for the cross-entropy loss in all experiments. We use the Adam optimizer for all modules. For the encoder and projection head, we use a learning rate of 10^{-4} and weight decay of 10^{-5}. For classifier, we use a learning rate of 10^{-3} and a weight decay of 10^{-3}. We use a batch size of 32 and train our method for 100 epochs. For all the modules, the learning rate is halved after every thirty epochs. We implement our method using the PyTorch framework, and use 4 GPUs for training each experiment. At test time, we use ten crops from temporally overlapping clips spanning the duration of the video and average their class probabilities to produce the final prediction.

4.3. Comparisons to state-of-the-art

We evaluate our method on the cross-subject and cross-view benchmarks on the widely used NTU-60 [50] and NTU-120 [37] datasets. We compare our method to state-of-the-art approaches using RGB information for multi-view action recognition on these benchmarks. We also compare with other methods that use additional input modalities, such as skeleton pose and depth, along with RGB. For unsupervised methods, we compare with the reported end-to-end fine-tuned results using class labels. In our experiments, at train time, we use the average probabilities of anchor and its corresponding synchronized views to get weights for negatives. We note that the predictions for multiple viewpoints of a given instance are not combined (which can lead to further improvements) to be consistent with prior works.

Results on NTU-60 [50] and NTU-120 [37]. In Tables 1 and 2, we show that our method consistently outperforms previous RGB-based methods on the cross-view and cross-subject benchmarks of both NTU-60 and NTU-120 datasets. On NTU-60, we show an improvement of 3.9% on the cross-view setting, demonstrating that features learned using our approach are more robust to viewpoint shifts. On the cross-subject benchmark, we improve upon the state-of-the-art by 1.7% showing the efficacy of our approach. On the larger NTU-120 dataset with more fine-grained activities, we observe improvements of 1.3% on the cross-setup benchmark and 1.1% on the cross-subject benchmark. We also report our 1-crop results in supplementary (Sec. 2) as some of the baselines ([57, 2, 21]) uses a single center crop at test time. Moreover, we also compare with methods using additional modality along with RGB, such as pose and depth. Significantly, in three of the four benchmarks, our RGB only method outperforms methods based on additional modalities. Similar to ViewCLR, we use AGCN [51] (joint stream only) to process the pose modality and perform late fusion of logits from both modalities. AGCN joint stream results in 94% on NTU-60 xview and 85.9% on NTU-60 xsub benchmarks. In Table 1, we see that our combined model leads to consistent improvements over single modality only. This shows that our RGB-based method extracts complementary information to pose-based AGCN.

Table 1: Comparison with state-of-the-art on cross-view (xview) and cross-subject (xsub) benchmarks of NTU-60 dataset. The proposed approach outperforms SotA approaches trained on RGB on both benchmarks. Fusion with pose modality leads to consistent improvements.

Method	Modality	NTU-60 (%) xview	xsub
STA-Hands [1]	RGB+Pose	88.6	82.5
Separable STA [10]	RGB+Pose	94.6	92.2
VPN [12]	RGB+Pose	96.2	93.5
ViewCLR[11]+Pose	RGB+Pose	97.0	92.9
Zhang *et al.* [68]	RGB	70.6	63.3
DA-Net [58]	RGB	75.3	–
Vyas *et al.* [57]	RGB	86.3	82.3
Debnath *et al.* [16]	RGB	–	87.2
Glimpse Clouds [2]	RGB	93.2	86.6
Piergiovanni *et al.* [43]	RGB	93.7	–
ViewCLR [11]	RGB	94.1	89.7
Ours	RGB	**98.0**	**91.4**
Ours+Pose	RGB+Pose	**98.9**	**93.7**

4.4. Transfer Learning

To show the generalization capability of features learned using our method, we show results on the smaller NUMA [60] dataset containing ten action classes. We report results on the cross-view benchmark. In this protocol, videos from cameras 1 and 2 are used for training and videos from camera 3 are used for testing. We initialize with weights from NTU-60 pre-trained models and fine-tune on NUMA dataset for 300 epochs. Table 3 reports accuracy on the cross-view setting for NUMA dataset. Our method improves by 2.6% over previous approaches, showing generalizability of our approach.

Table 2: Comparison with state-of-the-art on cross-setup (xset) and cross-subject (xsub) benchmarks of NTU-120 dataset. † uses RGB, flow and depth while training.

Method	Modality	NTU-120 (%) xset	NTU-120 (%) xsub
Hu *et al*. [27]	RGB + Depth	44.9	36.3
Hu *et al*. [26]	RGB + Depth	54.7	50.8
DMCL [21] †	RGB	84.3	–
Liu *et al*. [37]	RGB	54.8	58.5
ViewCLR [11]	RGB	86.2	84.5
Ours	RGB	**87.5**	**85.6**

Table 3: Accuracy on the cross-view benchmark of NUMA dataset. We significantly outperform other RGB-based methods on this dataset in the transfer learning setting.

Method	Modality	Accuracy (xview)
Li *et al*. [33]	RGB	62.5
Vyas *et al*. [57]	RGB	83.1
DA-Net [58]	RGB	86.5
ViewCLR [11]	RGB	89.1
Ours	RGB	**91.7**

4.5. Synthetic Data for Action Recognition

It can be difficult to collect and annotate activity videos, especially in a synchronized multi-view capture setting. In addition, collecting videos involving humans raises privacy concerns. We highlight that synthetic data [15] provides a practical alternative for creating custom multi-view action recognition datasets. Using a simulator, it is relatively easy to collect synchronized videos for each instance, with desired diversity and without any privacy issues. RoCoG [14] is a gesture recognition dataset consisting of videos from seven gestures. The dataset allows benchmarking on a realistic scenario where we have a large set of synthetic data collected from multiple viewpoints and a small set of real data for testing. For this dataset, we use the multi-view synthetic data for training and evaluate on real test data, and show that our method results in better domain generalization as opposed to standard cross-entropy training. We use the train/test split provided in [14].

We also compare our approach to a baseline that is trained on real data alone. This gives us the upper bound performance for models trained using synthetic data. Next we train the same backbone on synthetic data using the cross-entropy loss. This results in performance drop of 12.38%. Finally, we train using our proposed loss on synthetic data, and show that the domain gap reduces from 12.38% to 4.76%. The results of these experiments are presented in Table 4. The results show that features learned using our approach show much better domain generalization performance compared to standard loss function used for action recognition. These results, along with the transfer learning results show that our method can generalize well across different scenarios.

Table 4: Results on RoCoG dataset. In this experiment, models were trained using multi-view synthetic data and then evaluated on real data. This experiment helps show the domain generalization of the proposed approach. We show that our approach leads to an improvement of 7.6% over a standard classification baseline.

Method	Train	Test	Accuracy
Cross-Entropy	Real	Real	59.05
Cross-Entropy	Synthetic	Real	46.67
Ours	Synthetic	Real	54.29

4.6. Ablation Studies

We perform extensive ablation experiments to study the effect of different contributions and design choices of our method. All ablation experiments are performed on the cross-subject benchmark of NTU-60 dataset. We use a smaller dataset (NTU-60-small) for training, which consists of half of the subjects from the original cross-subject training set chosen randomly, and perform testing on the full test set of NTU-60 cross-subject benchmark.

Effect of View Contrastive Loss. We compare with different standard loss functions in Table 5 to show the effect of incorporating viewpoint information in the loss. Specifically, we train the same backbone models using cross-entropy, SupCon [29] and our loss functions. We can see that our loss function, which makes use of multi-view information, leads to better performance as expected. For our loss function (Eq. 4), we modify the SupCon loss (Eq. 2) by removing other positive samples from the denominator. We train our method using both variants (*i.e*. by keeping (Ours-A) and removing all other positives (Ours)) and show that the modified loss makes better use of multiple positives.

Effect of Hard Negatives. We show the effectiveness of our approach of incorporating hard negatives in the contrastive loss in Table 6. We train our model without using the re-weighting of hard negatives, *i.e*. setting weight of all negatives to one, giving them equal importance. From the table, we can see that incorporating hard negatives improves the performance over treating all negatives equally. We also compare with HCL [47], a recent method which proposes

Table 5: Effectiveness of the improved supervised contrastive loss. Compared to standard cross-entropy and SupCon, the loss function leads to higher accuracy. Ours-A uses all positives in denominator (as in SupCon) whereas Ours is the improved version. Models are trained on NTU-60-small training set.

Method	Accuracy (xsub)
Cross-Entropy	78.44
SupCon	78.47
Ours-A	78.89
Ours	79.75

Table 6: Effectiveness of our hard negative selection method on NTU-60-small. Compared to HCL, our method leads to better hard negatives. The proposed method selects all negative samples from hard classes, which is better than choosing a fixed number of hard classes.

Method	Accuracy (xsub)
HCL	78.86
Ours w/o hard negatives	79.43
Ours w/ top-3	79.54
Ours	79.75

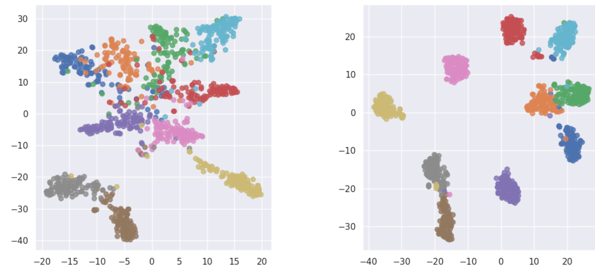
a way to use hard negatives in the contrastive loss for self-supervised setting. We train using their loss in our supervised setting, and show that our approach of using classifier probabilities for determining hardness leads to higher accuracy. Finally, we perform an experiment using only the top-3 negative classes of each anchor point and setting weight of other negatives to one. Note that our method uses all the hard samples which leads to better performance than only using the top-3 negative classes.

Sensitivity to viewpoints. The NTU-60 dataset has three views: front view, $\pm 45^\circ$ view and $\pm 90^\circ$ view (side view). To analyze the sensitivity to viewpoints, we perform three experiments, holding out a different test view in each, and training on the remaining views. We observe (Table 7) that testing on $\pm 45^\circ$ views (standard xview setting) is better compared to testing on front and side views. That said, the difference in performance is small which shows that our method is robust to different viewpoint configurations.

t-SNE Visualizations. We next visualize t-SNE embeddings for models trained using our approach. Fig. 4 compares visualizations of features from ten randomly chosen classes learned using ViewCon, which leverages multi-view data, with those of SupCon. We see that class clusters in our approach are better separated than those in SupCon. This further confirms the improved performance of our proposed ViewCon model.

Table 7: Effect of holding out different viewpoints. We conduct three experiments, holding out one viewpoint for testing and train on the remaining two views.

	Front view	$\pm 45^\circ$ view	$\pm 90^\circ$ view
Accuracy	97.1	98.0	96.9



(a) SupCon (b) ViewCon

Figure 4: t-SNE visualizations. In this figure, we visualize the t-SNE plots on ten classes of the NTU-60 test set for two approaches: SupCon and ViewCon. We can clearly see that our approach of incorporating view invariance and use of hard negatives improves the learned representations.

Please refer to the supplementary material to find single-crop results and details on data augmentations and RoCoG experiments.

5. Conclusion

In this work, we present an approach for multi-view action recognition. We make use of an improved version of supervised contrastive learning with the set of positives augmented by synchronized views of clips in addition to augmentations from the video. We also propose a novel technique to reweigh hard negatives guided by the classifier, thus learning learning richer feature representations. We demonstrate the superiority of our approach through comparisons on multi-view data from NTU-60, NTU-120 and NUMA. In addition, experiments on synthetic data from RoCoG show the generalizability nature of our approach.

6. Acknowledgements

The authors would like to thank Aniket Roy for helpful discussions. This research was sponsored by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-21-2-0211.

References

[1] Fabien Baradel, Christian Wolf, and Julien Mille. Human action recognition: Pose-based attention draws focus to hands. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 604–613, 2017.

[2] Fabien Baradel, Christian Wolf, Julien Mille, and Graham W. Taylor. Glimpse clouds: Human activity recognition from unstructured feature points. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

[3] Carlos Caetano, François Brémond, and William Robson Schwartz. Skeleton image representation for 3D action recognition based on tree structure and reference joints. In *2019 32nd SIBGRAPI conference on graphics, patterns and images (SIBGRAPI)*, pages 16–23. IEEE, 2019.

[4] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In *proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6299–6308, 2017.

[5] Hyuntak Cha, Jaeho Lee, and Jinwoo Shin. Co2l: Contrastive continual learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9516–9525, 2021.

[6] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, pages 1597–1607. PMLR, 2020.

[7] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. *arXiv preprint arXiv:2003.04297*, 2020.

[8] Yuxin Chen, Ziqi Zhang, Chunfeng Yuan, Bing Li, Ying Deng, and Weiming Hu. Channel-wise topology refinement graph convolution for skeleton-based action recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 13359–13368, 2021.

[9] Jinwoo Choi, Chen Gao, Joseph CE Messou, and Jia-Bin Huang. Why can't I dance in the mall? Learning to mitigate scene bias in action recognition. *Advances in Neural Information Processing Systems*, 32, 2019.

[10] Srijan Das, Rui Dai, Michal Koperski, Luca Minciullo, Lorenzo Garattoni, Francois Bremond, and Gianpiero Francesca. Toyota smarthome: Real-world activities of daily living. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

[11] Srijan Das and Michael S. Ryoo. Viewclr: Learning self-supervised video representation for unseen viewpoints, 2021.

[12] Srijan Das, Saurav Sharma, Rui Dai, Francois Bremond, and Monique Thonnat. Vpn: Learning video-pose embedding for activities of daily living. In *European Conference on Computer Vision*, pages 72–90. Springer, 2020.

[13] Alban Main De Boissiere and Rita Noumeir. Infrared and 3d skeleton feature fusion for rgb-d action recognition. *IEEE Access*, 8:168297–168308, 2020.

[14] Celso M de Melo, Brandon Rothrock, Prudhvi Gurram, Oytun Ulutan, and BS Manjunath. Vision-based gesture recognition in human-robot teams using synthetic data. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 10278–10284. IEEE, 2020.

[15] Celso M de Melo, Antonio Torralba, Leonidas Guibas, James DiCarlo, Rama Chellappa, and Jessica Hodgins. Next-generation deep learning based on simulators and synthetic data. *Trends in cognitive sciences*, 2021.

[16] Bappaditya Debnath, Mary O'brien, Swagat Kumar, and Ardhendu Behera. Attentional learn-able pooling for human activity recognition. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 13049–13055. IEEE, 2021.

[17] Michael Dorkenwald, Fanyi Xiao, Biagio Brattoli, Joseph Tighe, and Davide Modolo. Scvrl: Shuffled contrastive video representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4132–4141, 2022.

[18] Christoph Feichtenhofer. X3d: Expanding architectures for efficient video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 203–213, 2020.

[19] Christoph Feichtenhofer, Haoqi Fan, Jitendra Malik, and Kaiming He. Slowfast networks for video recognition. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 6202–6211, 2019.

[20] Rasha Friji, Hassen Drira, Faten Chaieb, Hamza Kchok, and Sebastian Kurtek. Geometric deep neural network using rigid and non-rigid transformations for human action recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 12611–12620, October 2021.

[21] Nuno Cruz Garcia, Sarah Adel Bargal, Vitaly Ablavsky, Pietro Morerio, Vittorio Murino, and Stan Sclaroff. Distillation multiple choice learning for multimodal action recognition. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 2755–2764, 2021.

[22] Michael Gutmann and Aapo Hyvärinen. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pages 297–304. JMLR Workshop and Conference Proceedings, 2010.

[23] Tengda Han, Weidi Xie, and Andrew Zisserman. Self-supervised co-training for video representation learning. *Advances in NIPS*, 33:5679–5690, 2020.

[24] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 9729–9738, 2020.

[25] Olivier Henaff. Data-efficient image recognition with contrastive predictive coding. In *International conference on machine learning*, pages 4182–4192. PMLR, 2020.

[26] Jian-Fang Hu, Wei-Shi Zheng, Jianhuang Lai, and Jianguo Zhang. Jointly learning heterogeneous features for RGB-D activity recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5344–5352, 2015.

[27] Jian-Fang Hu, Wei-Shi Zheng, Lianyang Ma, Gang Wang, Jianhuang Lai, and Jianguo Zhang. Early action prediction by soft regression. *IEEE transactions on pattern analysis and machine intelligence*, 41(11):2568–2583, 2018.

[28] Yannis Kalantidis, Mert Bulent Sariyildiz, Noe Pion, Philippe Weinzaepfel, and Diane Larlus. Hard negative mixing for contrastive learning. *Advances in Neural Information Processing Systems*, 33:21798–21809, 2020.

[29] Prannay Khosla, Piotr Teterwak, Chen Wang, Aaron Sarna, Yonglong Tian, Phillip Isola, Aaron Maschinot, Ce Liu, and Dilip Krishnan. Supervised contrastive learning. *Advances in Neural Information Processing Systems*, 33:18661–18673, 2020.

[30] Yu Kong, Zhengming Ding, Jun Li, and Yun Fu. Deeply learned view-invariant features for cross-view action recognition. *IEEE Transactions on Image Processing*, 26(6):3028–3037, 2017.

[31] Matthew Korban and Xin Li. Ddgcn: A directed graph convolutional network for action recognition. In *The European Conference on Computer Vision (ECCV)*, 2020.

[32] Matthew Kowal, Mennatullah Siam, Md Amirul Islam, Neil DB Bruce, Richard P Wildes, and Konstantinos G Derpanis. A deeper dive into what deep spatiotemporal networks encode: Quantifying static vs. dynamic information. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13999–14009, 2022.

[33] Junnan Li, Yongkang Wong, Qi Zhao, and Mohan S Kankanhalli. Unsupervised learning of view-invariant action representations. *Advances in neural information processing systems*, 31, 2018.

[34] Linguo Li, Minsi Wang, Bingbing Ni, Hang Wang, Jiancheng Yang, and Wenjun Zhang. 3D human action representation learning via cross-view consistency pursuit. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4741–4750, 2021.

[35] Yingwei Li, Yi Li, and Nuno Vasconcelos. Resound: Towards action recognition without representation bias. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 513–528, 2018.

[36] Ji Lin, Chuang Gan, and Song Han. Tsm: Temporal shift module for efficient video understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 7083–7093, 2019.

[37] Jun Liu, Amir Shahroudy, Mauricio Perez, Gang Wang, Ling-Yu Duan, and Alex C Kot. NTU RGB+D 120: A large-scale benchmark for 3D human activity understanding. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 42(10):2684–2701, 2020.

[38] Mengyuan Liu and Junsong Yuan. Recognizing human actions as the evolution of pose estimation maps. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

[39] Ziyu Liu, Hongwen Zhang, Zhenghao Chen, Zhiyong Wang, and Wanli Ouyang. Disentangling and unifying graph convolutions for skeleton-based action recognition. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 143–152, 2020.

[40] Diogo C Luvizon, David Picard, and Hedi Tabia. 2D/3D pose estimation and action recognition using multitask deep learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5137–5146, 2018.

[41] Rafael Müller, Simon Kornblith, and Geoffrey E Hinton. When does label smoothing help? *Advances in neural information processing systems*, 32, 2019.

[42] Vasu Parameswaran and Rama Chellappa. View invariance for human action recognition. *International Journal of Computer Vision*, 66(1):83–101, 2006.

[43] AJ Piergiovanni and Michael S. Ryoo. Recognizing actions in videos from unseen viewpoints. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4124–4132, June 2021.

[44] Rui Qian, Tianjian Meng, Boqing Gong, Ming-Hsuan Yang, Huisheng Wang, Serge Belongie, and Yin Cui. Spatiotemporal contrastive video representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6964–6974, 2021.

[45] Hossein Rahmani, Arif Mahmood, Du Huynh, and Ajmal Mian. Histogram of oriented principal components for cross-view action recognition. *IEEE transactions on pattern analysis and machine intelligence*, 38(12):2430–2443, 2016.

[46] Hossein Rahmani, Ajmal Mian, and Mubarak Shah. Learning a deep model for human action recognition from novel viewpoints. *IEEE transactions on pattern analysis and machine intelligence*, 40(3):667–681, 2017.

[47] Joshua Robinson, Ching-Yao Chuang, Suvrit Sra, and Stefanie Jegelka. Contrastive learning with hard negative samples. *International Conference on Learning Representations*, 2021.

[48] Aadarsh Sahoo, Rutav Shah, Rameswar Panda, Kate Saenko, and Abir Das. Contrast and mix: Temporal contrastive video domain adaptation with background mixing. *Advances in Neural Information Processing Systems*, 34, 2021.

[49] Anshul Shah, Suvrit Sra, Rama Chellappa, and Anoop Cherian. Max-margin contrastive learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 8220–8230, 2022.

[50] Amir Shahroudy, Jun Liu, Tian-Tsong Ng, and Gang Wang. NTU RGB+D: A large scale dataset for 3D human activity analysis. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1010–1019, 2016.

[51] Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. Two-stream adaptive graph convolutional networks for skeleton-based action recognition. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 12026–12035, 2019.

[52] Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. Decoupled spatial-temporal attention network for skeleton-based action-gesture recognition. In *Proceedings of the Asian Conference on Computer Vision*, 2020.

[53] Lei Shi, Yifan Zhang, Jian Cheng, and Hanqing Lu. AdaSGN: Adapting joint number and model size for efficient skeleton-based action recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 13413–13422, 2021.

[54] Karen Simonyan and Andrew Zisserman. Two-stream convolutional networks for action recognition in videos. *Advances in neural information processing systems*, 27, 2014.

[55] Pavan Turaga, Rama Chellappa, Venkatramana S Subrahmanian, and Octavian Udrea. Machine recognition of human activities: A survey. *IEEE Transactions on Circuits and Systems for Video technology*, 18(11):1473–1488, 2008.

[56] Pavan Turaga, Ashok Veeraraghavan, Anuj Srivastava, and Rama Chellappa. Statistical computations on Grassmann and Stiefel manifolds for image and video-based recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(11):2273–2286, 2011.

[57] Shruti Vyas, Yogesh S Rawat, and Mubarak Shah. Multi-view action recognition using cross-view video prediction. In *European Conference on Computer Vision*, pages 427–444. Springer, 2020.

[58] Dongang Wang, Wanli Ouyang, Wen Li, and Dong Xu. Dividing and aggregating network for multi-view action recognition. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 451–467, 2018.

[59] Jinpeng Wang, Yuting Gao, Ke Li, Yiqi Lin, Andy J Ma, Hao Cheng, Pai Peng, Feiyue Huang, Rongrong Ji, and Xing Sun. Removing the background by adding the background: Towards background robust self-supervised video representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11804–11813, 2021.

[60] Jiang Wang, Xiaohan Nie, Yin Xia, Ying Wu, and Song-Chun Zhu. Cross-view action modeling, learning and recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2649–2656, 2014.

[61] Philippe Weinzaepfel and Grégory Rogez. Mimetics: Towards understanding human actions out of context. *International Journal of Computer Vision*, 129(5):1675–1690, 2021.

[62] Chao-Yuan Wu, Ross Girshick, Kaiming He, Christoph Feichtenhofer, and Philipp Krahenbuhl. A multigrid method for efficiently training video models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 153–162, 2020.

[63] Xinxiao Wu, Dong Xu, Lixin Duan, and Jiebo Luo. Action recognition using context and appearance distribution features. In *CVPR 2011*, pages 489–496. IEEE, 2011.

[64] Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy. Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification. In *Proceedings of the European conference on computer vision (ECCV)*, pages 305–321, 2018.

[65] Shen Yan, Xuehan Xiong, Anurag Arnab, Zhichao Lu, Mi Zhang, Chen Sun, and Cordelia Schmid. Multiview transformers for video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3333–3343, 2022.

[66] Manlin Zhang, Jinpeng Wang, and Andy J Ma. Suppressing static visual cues via normalizing flows for self-supervised video representation learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 3300–3308, 2022.

[67] Pengfei Zhang, Cuiling Lan, Junliang Xing, Wenjun Zeng, Jianru Xue, and Nanning Zheng. View adaptive neural networks for high performance skeleton-based human action recognition. *IEEE transactions on pattern analysis and machine intelligence*, 41(8):1963–1978, 2019.

[68] Pengfei Zhang, Jianru Xue, Cuiling Lan, Wenjun Zeng, Zhanning Gao, and Nanning Zheng. Adding attentiveness to the neurons in recurrent neural networks. In *proceedings of the European conference on computer vision (ECCV)*, pages 135–151, 2018.

[69] Jingjing Zheng, Zhuolin Jiang, P Jonathon Phillips, and Rama Chellappa. Cross-view action recognition via a transferable dictionary pair. In *bmvc*, volume 1, page 7, 2012.

[70] Yi Zhu, Xinyu Li, Chunhui Liu, Mohammadreza Zolfaghari, Yuanjun Xiong, Chongruo Wu, Zhi Zhang, Joseph Tighe, R Manmatha, and Mu Li. A comprehensive study of deep video action recognition. *arXiv preprint arXiv:2012.06567*, 2020.

[71] Mohammadreza Zolfaghari, Gabriel L Oliveira, Nima Sedaghat, and Thomas Brox. Chained multi-stream networks exploiting pose, motion, and appearance for action classification and detection. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2904–2913, 2017.