When Video Classification Meets Incremental Classes

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ABSTRACT

With the rapid development of social media, tremendous videos with new classes are generated daily, which raise an urgent demand for video classification methods that can continuously update new classes while maintaining the knowledge of old videos with limited storage and computing resources. In this paper, we summarize this task as Class-Incremental Video Classification (CIVC) and propose a novel framework to address it. As a subarea of incremental learning tasks, the challenge of catastrophic forgetting is unavoidable in CIVC. To better alleviate it, we utilize some characteristics of videos. First, we decompose the spatio-temporal knowledge before distillation rather than treating it as a whole in the knowledge transfer process; trajectory is also used to refine the decomposition. Second, we propose a dual granularity exemplar selection method to select and store representative video instances of old classes and key-frames inside videos under a tight storage budget. We benchmark our method and previous SOTA class-incremental learning methods on Something-Something V2 and Kinetics datasets, and our method outperforms previous methods significantly.

CCS CONCEPTS

• Computing methodologies → Activity recognition and understanding.

KEYWORDS

Video classification, class-incremental, action recognition

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1 INTRODUCTION

Recent years have witnessed an immense explosion of multimedia data, especially videos, due to the rapid development of social network applications (e.g., Instagram, TikTok). Meanwhile, deep learning boosts the development of video understanding [3, 30, 44, 58]. Previous works on video understanding and analysis achieve outstanding performance with the fixed number of video classes during training. However, it is usually not the case in real-world applications where new video classes emerge continuously. For example,
there are millions of short videos, along with new classes (e.g., themes or tags), shared by users in social media daily. The video understanding model is required to adapt to those new classes.

An intuitive solution to recognize all classes is to mix all videos from both old and new classes and train a new model from scratch. Unfortunately, it is infeasible to train a model from scratch repeatedly every time new classes of videos emerge as the computation overhead is unaffordable. Also, maintaining such a huge dataset for training raises a great challenge in storage resources. An alternative is to fine-tune the old model using videos of new classes. In this way, the model achieves good performance on new video classes; however, a significant performance drop on old classes occurs (such a phenomenon is called catastrophic forgetting [33]). Therefore, there is a significant interest of research in training a model with high performance on both old and new videos on a tight budget in both storage and computation resources. Among those video understanding tasks, we focus on video classification in this paper, and thus we name this problem as: Class-Incremental Video Classification (CIVC) (as shown in Figure 1).

CIVC, as a first proposed task, is related to Class-Incremental Image Classification (CIIC), which is a widely explored area. In CIIC, previous methods tackle the forgetting problem in two ways: 1) transferring the old-class knowledge while learning the new-class knowledge, usually involved with distillation, and 2) utilizing a limited memory to select and store a few most representative old-class images. In contrast to images that contain only spatial information, videos are much more complicated as they convey intricate spatio-temporal information; meanwhile, videos comprise a sequence of frames, each of which is an image. Hence, based on the above two characteristics of videos, we improve the CIIC method to better fit CIVC task according to the following two strategies: 1) the decomposed spatial-temporal knowledge transfer mechanism, where the spatial-temporal knowledge is decomposed and then distilled separately; 2) the dual granularity exemplars selection, which not only selects exemplars at video granularity but also selects the key-frames inside video exemplars, i.e., inner-video granularity.

First, we develop an effective knowledge transfer strategy handling the spatio-temporal knowledge conveyed in videos. Due to the different characteristics of spatial information and temporal information, we observe that directly distilling the fused spatio-temporal feature transfers less knowledge than distilling the spatial and temporal feature separately (as shown in Figure 2). Hence, we claim that the spatial and temporal feature should be decomposed before distillation. A naive decomposition by pooling on different spatio-temporal dimensions has achieved improvement on performance by a tolerable margin; utilizing trajectory, which is considered as key temporal knowledge in videos [49, 63], to refine the decomposition achieves a better distillation quality.

Second, we propose to select the most representative samples at two granularity (i.e., instance-granularity and inner-instance-granularity). As mentioned above, a video is a sequence of images, where some images that play remarkable roles in the temporal sequence can be selected as key-frames. Therefore, besides sampling at video instance-granularity, we also select key-frames from representative videos base on the temporal information. By preserving the most informative frames in the most representative videos, the memory budget for storing the videos is further compressed.

In order to acquire a more convincing assessment, we build the CIVC baselines by adapting the state-of-the-art CIIC methods to this new task and compare our method with them. We illustrate the effectiveness of our proposed framework by extensive evaluation on popular video classification benchmarks, Something-Something V2 and Kinetics.

The contributions of this paper can be summarized as follows:

- We establish the CIVC task and propose the corresponding framework. We benchmark our method and previous SOTA class-incremental learning methods on two popular video classification datasets under different experimental settings.
- We design a novel knowledge transfer approach that ingeniously decomposed the fused spatio-temporal feature with the help of trajectory before distillation. The decomposition has a significant performance improvement.
- We design a simple yet effective dual granularity exemplars selecting strategy that selects and stores the key-frames of most representative video exemplars. This strategy reduces the memory budget by a large margin.

2 RELATED WORK
2.1 Video Classification

With the rise of deep learning, CNNs dominated the video understanding literature recently [3, 21, 27, 30, 36, 44, 54, 56], instead of hand-crafted features [1, 26, 35, 46, 47]. Since video understanding
intuitively needs motion information, finding an appropriate way to
describe the temporal relationship between frames is essential
to improving the performance of video classification. Hence, two-
stream networks [41] which include a spatial stream and a temporal
stream are proposed. The spatial stream takes raw video frames
as input to capture visual appearance information. The temporal
stream takes a stack of optical flow images as input to capture
motion information between video frames. It is the first time, a
CNN-based approach achieved performance similar to the previ-
ous best hand-crafted feature IDT [47]. After that, a large number
of improvements have been made based on this work, eg, using
deeper networks [16], preventing networks from overfitting [50],
fusing two-stream features better [12–14, 52], and multi-stream
network [57].

However, pre-computing optical flow is computationally in-
tensive and storage demanding, which is not friendly for large-
scale training or real-time deployment. Hence, this leads to the
usage of 3D CNN to model the temporal and spatial information
together [4, 20, 43]. Although the performance of C3D [43] on
standard benchmarks is not satisfactory, but it shows strong gen-
eralization capability. iSD [4] inflates the ImageNet pre-trained
2D model weights to their counterparts in the 3D model, and pre-
trained on a new large-scale dataset, Kinetics400, getting the best
classification accuracy and pushing this task to the next level.
In the next few years, 3D CNNs advanced quickly and became top per-
formers on almost every benchmark dataset [10, 11, 51]. To reduce
the complexity of 3D network training, many works factorize the
3D kernel to two separate operations (i.e., a 2D spatial convolution
and a 1D temporal convolution) [37, 45, 59], or mix 2D and 3D
convolutions in a single network [48, 59, 65, 66]. Recently, many
works perform temporal modeling with an extra module instead
of the simple 1D temporal convolution [22, 28, 30, 32, 39]. All the
above works focus on the traditional video classification scenario
where all classes of data are available when training the models.
Our work focuses on the CIVC scenario where new video classes
emerges continuously.

2.2 Class-Incremental Image Classification

Recently, there has been a large body of research in class-incremental
image classification [7, 61]. These works mainly tackle the forgetting
problem by effective old-class knowledge transfer and utilize
a limited memory to keep exemplars of old classes. As for effec-
tive knowledge transfer, LWF [29] first applies knowledge distilla-
tion [17] to alleviate the forgetting problem. iCaRL [38] combines
the idea and compute the distillation loss on the prediction of the
network. EEIL [5] extends iCaRL by learning the network and clas-
sifier with an end-to-end approach. BiC [55] tried to balance the
classifier by a bias correction layer, where the layer is trained on a
separate validation set. LUCIR [18] also introduces multiple tech-
niques to correct the classifier. PODNet [9] utilizes a spatial-based
distillation loss to restrict the change of model. TPCIL [42] makes
the model preserve the topology of CNN’s feature space. As for
keeping the exemplars, iCaRL proposes to replay old knowledge
with a handful of herding exemplars. Herding [53] picks the near-
est neighbors of the average sample per class. The same herding
exemplars are also utilized in multiple works [5, 18, 19, 55, 62],

Some methods [23, 31, 40] utilize synthesized exemplars by image
synthesis models. The performance of these methods depend on
the image synthesis models, so they require a large extra computa-
tion overhead to optimize the image synthesis models and might
not be applicable in practical CIC with a strict computation bud-
get. All of the above works focus on class-incremental image-level
classification. Our work is the first work which considers the class-
incremental video-level classification. In this work, we establish
CIVC and propose to address the forgetting problem by video-level
effective old-class knowledge transfer and efficient old-class exemplars keeping.

3 METHOD

3.1 Video Classification

Before delving into the details of CIVC, we first introduce the task
of video classification. Given a category set L, we have a video
data set \( D = \{(V_i, y_i), y_i \in L\} \) and each video sample is composed
of a set of frames \( V_i = \{ V_{i,t} \}_{t=1}^{W_i} \). A video classification model \( F(\Theta) \)
with parameters \( \Theta \) is composed of a feature extractor \( f(\cdot; \Theta) \) and
a classifier with parameters \( \phi \). Given a video sample \( V \), the feature map of the video sample \( f(V;\Theta) \) is a \( C \times T \times H \times W \) tensor where \( C \) is the number of channels and \( T, H, W \)
are the temporal and spatial dimensions. Let tensor \( x_t \in \mathbb{R}^{C \times H \times W} \) denotes the feature map of frame \( \phi \) in the video \( V \). \( \Theta \) is optimized
on \( D \) by the following loss function:

\[
L(\Theta) = L_{CE}(\Theta),
\]

where \( L_{CE} \) is a cross-entropy loss.

3.2 Class-Incremental Video Classification

We define CIVC as follows. Assume the datasets \( D^1, D^2, \ldots \)
in a data stream arrive in order and \( D^k = \{(V_{i}^k, y_{i}^k), y_{i}^k \in L^k\} \) arrives at
the \( k \)-th training session, where \( V_{s}, q, s \neq q \Rightarrow L^s \cap L^q = \emptyset \). At the
first training session, \( D^1 \) arrives (considered as the base dataset) and
\( \Theta^1 \) is trained from scratch on \( D^1 \) by Equ. (1). Then as \( D^k \) appears
at the \( k \)-th session (\( k > 1 \)), our goal is to obtain a model \( F(\Theta^k) \)
which recognizes all encountered classes in \( L^1, L^2, \ldots, L^k \) well.

To achieve this goal, a simple way is keeping all the encounter-
datasets \( D^1, D^2, \ldots, D^k \) and training the model \( F(\Theta^k) \) from scratch on
the mixed dataset at the \( k \)-th session. However, it is impractical
because training the model from scratch repeatedly on the large-
scale mixed video dataset requires huge computation and storage
overhead. Another way is directly fine-tuning the model \( F(\Theta^k) \)
initialized by \( \Theta^{k-1} \) on the dataset \( D^k \), which can greatly reduce
the overall training overhead. But this method leads to the perform-
ance degradation of the model \( F(\Theta^k) \) on previous classes (ie,
catastrophic forgetting). To meet the demand of real-world applica-
tions, we need to maintain the performance on previous video
classes as well as reduce the overall overhead for training.

Existing CiC works maintain the performance on previous classes
by knowledge distillation, and reduce the overall overhead by
keeping only a few representative samples from the old datasets
in a limited memory buffer \( M \). Taking the \( k \)-th session as an exam-
ple, these methods usually keep few exemplars \( M^{k-1} \) drawn from
previous datasets \( D^1, \ldots, D^{k-1} \) and updating \( \Theta^k \) by transferring
knowledge from $\Theta^{k-1}$. The approach for knowledge transfer and exemplar selection are introduced as follows.

**Knowledge Transfer.** To transfer the knowledge from the model $F(; \Theta^{k-1})$, the distillation loss term $L_{KD}$ is added to the loss function while optimizing the model $F(; \Theta^k)$:

$$L^k(\Theta^k) = L_{CE}(\Theta^k) + \gamma L_{KD}(\Theta^k),$$

where $\gamma > 0$ is a hyper-parameter balancing the importance of the loss terms. The distillation loss is utilized to maintain the performance on previous classes and conducted in both the feature extractor and the classifier:

$$L_{KD}(\Theta^k) = L_{FKD}(\Theta^k) + \alpha L_{cKD}(\Theta^k),$$

where $L_{FKD}$ and $L_{cKD}$ is the feature distillation loss and classifier distillation loss respectively. The implementation for $L_{FKD}$ takes the form:

$$L_{FKD}(\Theta^k) = \sum_{(V, y) \in D^k \cup M^{k-1}} \| f(V; \Theta^{k-1}) - f(V; \Theta^k) \|^2.$$  

where $\| \cdot \|$ denotes the Euclidean distance. As for $L_{cKD}(\Theta^k)$, a general form of implementation can be formulated as:

$$L_{cKD}(\Theta^k) = \sum_{(V, y) \in D^k \cup M^{k-1}} \sum_{i=1}^{n} -\delta_i(V; \Theta^{k-1}) \log(\delta_i(V; \Theta^k)),$$

$$\delta_i(V; \Theta^k) = \frac{e^{F_i(V; \Theta^k)}}{\sum_{j=1}^{n} e^{F_j(V; \Theta^k)}},$$

where $n = \sum_{i=1}^{k-1} |L^i|$ is the number of the old classes and $TP$ is the distillation temperature.

**Exemplar Selection.** After updating the model $F(; \Theta^k)$, a common implementation first utilizes the feature extractor $f(; \Theta^k)$ to extract the feature for each video $V_i^k$ in $D^k$. For each class $c_{mn}$ in $L^k$, the class center $U_{cm}$ is obtained by computing the mean of all samples’ features. Then the samples of each class $c_{mn}$ are sorted according to their distances to the class center in ascending order. As a result, a class-specific ranking list is obtained for each class $c_{mn}$. The top $K$
Temporal Features

To achieve effective knowledge transfer, we propose a video-tailored feature distillation loss respectively, and temporal feature decompose function respectively. Then at the encoded spatio-temporal knowledge transfer scheme in Section 3.3 and a dual granularity exemplar selection scheme in Section 3.4. The illustration of our scheme for CIVC is shown in Figure 3.

3.3 Decomposed Spatio-Temporal Knowledge Transfer

To achieve effective knowledge transfer, we propose a video-tailored decomposed spatio-temporal knowledge transfer approach. We observe that directly distilling the fused spatio-temporal feature achieves less knowledge transfer than distilling the spatial and temporal features separately (as shown in Figure 2).

In order to transfer the spatial knowledge and temporal knowledge separately, we first need to decompose the fused spatio-temporal feature of a video sample to a spatial feature and a temporal feature. For simplicity, we utilize $\Phi_{sf}()$ and $\Phi_{tf}()$ to denote the spatial and temporal feature decompose function respectively. Then at the $k$-th session, the feature distillation loss in Equ. (3) is conducted for both the spatial feature and temporal feature:

$$L_{FKD}(\theta^k) = L_{sfK}(\theta^k) + \lambda L_{tfK}(\theta^k), \tag{6}$$

where $L_{sfK}$ and $L_{tfK}$ are the spatial feature and temporal feature distillation loss respectively, $\lambda$ is a hyper-parameter balancing the importance of the spatial and temporal feature distillation loss. $L_{sfK}$ and $L_{tfK}$ takes the similar form in Equ. (4):

$$L_{sfK}(\theta^k) = \sum_{(V,y) \in D^k, \cup M^{k-1}} \left\| \Phi_{sf}(f(V; \theta^{k-1})) - \Phi_{sf}(f(V; \theta^k)) \right\|^2, \tag{7}$$

$$L_{tfK}(\theta^k) = \sum_{(V,\tau)\in D^k, \cup M^{k-1}} \left\| \Phi_{tf}(f(V; \theta^{k-1})) - \Phi_{tf}(f(V; \theta^k)) \right\|^2.$$
where $\{w_i : \tau \in [-\Delta t, \Delta t]\}$ are the parameters of the filter with kernel size $(2\Delta t + 1)$. The point $p_t$ at frame $t$ can be tracked to position $\bar{p}_{t+1}$ at next frame $t+1$ using the following equation:

$$\bar{p}_{t+1} = p_t + \sigma (p_t),$$

where $\sigma (p_t)$ denotes a forward dense motion field of $p_t$ [63]. For $\tau > 1$, the sample position $\bar{p}_{t+1}$ can be calculated by applying Eq. (10) iteratively. To track the previous frame $t-1$, a backward dense motion field $\sigma (p_t)$ is used likewise.

Moreover, the trajectory information itself can be considered as a temporal information pattern [47] and then we leverage the trajectory information while implementing $\Phi_{tf}(\cdot)$:

$$\Phi_{tf}(f(V; \theta^k)) = TrajTemp(f(V; \theta^k)),$$

where $TrajTemp(\cdot)$ denotes the trajectory-based temporal feature transformation function. Specifically, the trajectory-based temporal feature transformation function describes the local temporal information pattern of $x_t$ at frame $t$ [47], and then transform the local temporal information of $x_t$ (i.e., the concatenation of $\sigma (p_t)$ and $\sigma (p_t)$) to a temporal feature by convolution operation (shown in Figure 5).

3.4 Dual Granularity Exemplar Selection

In this section, we propose a video-tailored dual granularity exemplar selection approach to reduce the memory overhead. Existing CIIC methods focus on selecting representative samples at the instance granularity. However, being different from images, a video comprises a number of frames and each frame itself is an image. Therefore, we further investigate the representative at the inner-instance granularity.

At each session, we first select the representative samples from the instance-granularity and the top $K$ samples are selected as the exemplars. As videos are comprised of a sequence of consistent frames, the information contained in neighbor frames may densely overlap and thus can be regarded as redundant information. The redundant information of multiple video frames can be reduced by keeping only a few key-frames. Suppose there is a video exemplar $v_i$ and a frame $v_j$ ($i < j$). Specifically, the distance function is defined as follows:

$$\text{Dis}(v_i, v_j) = \|v_i - v_j\|^2.$$

If the distance between $v_i$ and $v_j$ is smaller than the threshold $\text{Thre}$, we keep the key-frame set unchanged; if the distance is larger than the threshold, the current frame is added to the key-frame set and the newest key-frame is now pointed to this frame, as illustrated in Figure 6:

$$\text{Thre} = \beta_{\text{thre}} \sum_{i=1}^{V-1} \text{Dis}(v_i, v_{i+1}).$$

where $\beta_{\text{thre}}$ is a hyper-parameter which can affect the memory overhead for keeping exemplars.

4 EXPERIMENTS

4.1 Datasets

For the task of video classification, existing datasets can be roughly divided into two groups: YouTube-type videos and crowd-sourced videos [58, 64]. Crowd-sourced videos usually focus more on modeling the temporal relationships, since visual contents among different classes are more similar than those of YouTube-type videos. We select two popular large-scale video classification datasets Something-Something V2 [15] (i.e., Sth-Sth) and Kinetics [24] and conduct comprehensive experiments on them. Something-Something V2 is a crowd-sourced video dataset that includes 220k video clips for 174 fine-grained classes; Kinetics is a YouTube-type video dataset that contains 400 human action categories and provides 240k training videos and 20k validation videos. We utilize these two datasets to construct the CIVC benchmarks in Section 4.2.

4.2 Benchmark and Evaluation Protocol

**Benchmark.** Four CIVC benchmarks are constructed on Something-Something V2 and Kinetics: 1) i-Something-Something-B0: selecting a subset of 40 classes from Something-Something V2, where all 40 classes are divided into 4 splits and trained in 4 training sessions. 2) i-Something-Something-B20: utilizing a subset of 40 classes from Sth-Sth V2, where the model is trained on 20 classes first and the remaining 20 classes are divided into 5 sessions. 3) i-Kinetics-B0: randomly selecting a subset of 40 classes from Kinetics, where all 40 classes are divided into 4 splits and trained in 4 sessions. 4) i-Kinetics-B20: selecting a subset of 40 classes from Kinetics randomly, where the model is first trained with 20 classes and the remaining 20 classes are divided into 5 training sessions.

**Evaluation protocol.** Each method is trained on the CIVC benchmark in several sessions. At the end of each session, we report the classification accuracy of the trained model $F(\cdot; \Theta^k)$ on the test part.
We follow the video preprocessing procedure introduced in TSN [50]. The whole training procedure takes 25 epochs. The loss weights on ImageNet [8] are set to 0.05 respectively. The motion field and are all set to 1. The distillation temperature TP is set to 2, and the number of exemplars per class is set to 10 unless otherwise stated. For a fair comparison, the training setting and backbone are the same for all methods. The hyper-parameter $\beta_{thre}$ on i-Sth-Sth and i-Kinetics is set to 0.9 and 1.05 respectively. The motion field $\sigma$ is often represented by dense optical flow in previous works [46, 47, 49]. Since calculating optical flow is too time-consuming, we integrate a learnable module to quickly calculate the approximate optical flow [25].

### Table 1: Validation of decomposed spatio-temporal knowledge transfer scheme and dual granularity exemplar selection.

| Method               | i-Sth-Sth-B0 | i-Sth-Sth-B20 | i-Kinetics-B0 | i-Kinetics-B20 |
|----------------------|--------------|---------------|---------------|---------------|
|                       | Acc.(%)      | Forget.(%)    | Mem.(G)      | Acc.(%)       | Forget.(%)    | Mem.(G)      | Acc.(%)       | Forget.(%)    | Mem.(G)      |
| Baseline             | 40.79        | 40.60         | 0.61          | 34.45         | 43.15         | 0.61          | 51.26         | 30.49         | 3.30          |
| Baseline+decomposed-pool | 45.87     | 33.60         | 0.61          | 38.83         | 36.20         | 0.61          | 56.78         | 25.51         | 3.30          |
| Baseline+decomposed-traj | 46.30    | 32.70         | 0.61          | 40.04         | 35.55         | 0.61          | 57.65         | 24.73         | 3.30          |
| Baseline+dual-gra    | 40.35        | 41.24         | 0.44          | 34.08         | 43.46         | 0.44          | 51.97         | 30.92         | 1.52          |

Baseline. Our main baseline is given based on a classical CIIC method EEIL [5], which selects exemplars of previously seen classes only from the instance-granularity and maintains the performance on previous classes by the classifier distillation loss. All experiments are reported with our implementation unless specified otherwise. The original EEIL fixes the total number of exemplars stored at any session, and changes the number of exemplars per class depending on the total number of classes. Unlike the original EEIL, we fix the number of exemplars per class as in our implementation. We extend the original implementation of EEIL by applying a fused spatio-temporal feature distillation loss as the variant has been shown to improve the accuracy. We refer to the resulting variant as our "Baseline".

**Effect of our decomposed spatio-temporal knowledge transfer scheme.** In order to demonstrate the effectiveness of our decomposed spatio-temporal Knowledge transfer scheme, we compare the performance of "Baseline" with our decomposed spatio-temporal knowledge transfer scheme (denoted by "Baseline + decomposed"). The curves of accuracy are shown in Figure 2. We can see that the accuracy of "Baseline+decompose" surpasses that of "Baseline" at every session for different benchmarks. Moreover, the gap between "Baseline + decomposed" and "Baseline" increases with continuous adding of novel classes. In particular, the accuracy of "Baseline + decompose" outperforms "Baseline" by around 6% at the last session on i-Kinetics-B20. This result indicates that distilling the spatial and temporal feature separately achieves more effective knowledge transfer than directly distilling the fused spatio-temporal feature.

**Different decomposed spatio-temporal knowledge transfer implementations.** We evaluate the decomposed spatio-temporal knowledge transfer scheme with a simple pooling-based implementation (denoted by "Baseline + decomposed-pool") and a complex trajectory-based implementation (denoted by "Baseline + decomposed-traj"). We compare the performance of "Baseline + decomposed-traj" and "Baseline + decomposed-pool" and the results are shown in Table 1. It is observed that the accuracy of Baseline + decomposed-traj outperforms that of Baseline + decomposed-pool for all benchmarks. Moreover, Baseline + decomposed-traj achieves less forgetting rate than Baseline + decomposed-pool.

**Effect of our dual granularity exemplar selection scheme.** We evaluate the performance of "Baseline" with our dual granularity exemplar selection scheme (denoted by "Baseline + dual-gra") and Table 1 summarizes the experimental results for different benchmarks. We can see that "Baseline + dual-gra" achieves similar performance with fewer memory overhead than "Baseline". In particular, "Baseline + dual-gra" achieves similar accuracy than "Baseline" with only half of the memory overhead on i-Kinetics-B0.
Table 2: Accuracy, forgetting rate and memory overhead of different methods on the four CIVC benchmarks.

| Method       | i-Sth-Sth-B0 | i-Sth-Sth-B20 | i-Kinetics-B0 | i-Kinetics-B20 |
|--------------|--------------|--------------|--------------|---------------|
|              | Acc. (%) | Forget. (%) | Mem. (G) | Acc. (%) | Forget. (%) | Mem. (G) | Acc. (%) | Forget. (%) | Mem. (G) | Acc. (%) | Forget. (%) | Mem. (G) |
| FT-Lower Bound | 11.52  | 78.20  | 0.00    | 7.62  | 71.00  | 0.00    | 21.25  | 83.47  | 0.00    | 8.37  | 82.83  | 0.00    |
| iCaRL [38]   | 34.37  | 74.53  | 0.61    | 30.16  | 86.10  | 0.61    | 44.67  | 71.63  | 3.30    | 41.89  | 69.38  | 3.30    |
| EEIL [5]     | 39.43  | 47.62  | 0.61    | 31.60  | 46.44  | 0.61    | 51.43  | 36.47  | 3.30    | 47.79  | 33.34  | 3.30    |
| BiC [55]     | 41.70  | 42.50  | 0.61    | 33.24  | 44.00  | 0.61    | 54.62  | 34.29  | 3.30    | 50.26  | 28.15  | 3.30    |
| PODNet [9]   | 42.07  | 37.36  | 0.61    | 35.98  | 40.62  | 0.61    | 53.90  | 28.98  | 3.30    | 51.03  | 24.90  | 3.30    |
| Ours (ST)    | 46.03  | 31.72  | 0.44    | 39.73  | 34.75  | 0.44    | 57.26  | 25.50  | 1.52    | 54.24  | 22.90  | 1.52    |
| Ours (SM)    | 48.17  | 30.72  | 0.61    | 45.84  | 32.25  | 0.61    | 60.21  | 19.59  | 3.30    | 60.41  | 18.90  | 3.30    |

Joint-Upper Bound | 64.65  | -      | 61.04   | 64.65  | -      | 61.04   | 72.95  | -      | 248.81  | 72.95  | -      | 248.81  |

Figure 7: The accuracy curves of different methods on the four CIVC benchmarks.

This result indicates that the inner-instance granularity key-frames selection is essential to reduce the memory overhead for CIVC.

4.5 Comparison to State-of-the-Art Methods

In this section, we evaluate the CIVC performance of our proposed method on the four benchmarks, against other standard CIIC methods on the considered CIVC task, including iCaRL [38], EEIL [5], BiC [55] and PODNet [9]. In the tables, we also report other two methods: simple fine-tuning $F_i(\Theta_k)$ on $D_k$ (denoted by "FT") and training the model on all classes off-line (denoted by "Joint"). The former can be considered as a lower bound and the latter can be regarded as an upper bound.

Table 2 summarizes the experimental results for the four CIVC benchmarks. We can see that the average accuracy of our method consistently outperforms that of other methods by a sizable margin on different benchmarks. As for the memory overhead, "Joint" keeps all previous datasets in memory and thus utilizes the largest memory overhead. iCaRL, EEIL and PODNet all select a fixed number of video exemplars per class from the instance-granularity and they utilize the same size of memory overhead. Our method first selects the same number of video exemplars and then keeps a small number of key-frames in memory from dual granularity and achieves lower memory overhead (denoted by "Ours (ST)"). It is worth noting that our method with the same size of memory overhead (denoted by "Ours (SM)") can further improve the performance. The overview on forgetting rates reveals that our approach is greatly helpful to maintain the performance on previous classes. For example, the forgetting rate of "Ours (SM)" is 6.64% less than that of PODNet on i-Sth-Sth-B0 (8.37% on i-Sth-Sth-B20, 9.39% on i-Kinetics-B0, 6.00% on i-Kinetics-B20). The accuracy curves of these methods are shown in Figure 7. We can see that our method consistently surpasses the other methods for all training sessions on each benchmark. As the number of training sessions increases, it is observed that the margin between our method with other methods continuously increases, which indicates our method performs better on the benchmark with more number of training sessions.

5 CONCLUSION

In this paper, we propose the task of Class-Incremental Video Classification and design a novel framework for it. Our model inherits knowledge from old class videos effectively with the decomposed spatial-temporal knowledge transfer mechanism. By selecting both the video exemplars and key-frames inside the videos, we greatly reduce the storage memory and preserve the most representative information of old classes. Lastly, we establish the benchmark for this task and perform intensive evaluations of our method and other SOTA class-incremental learning methods, showing the effectiveness of our method.

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