Label-Efficient Online Continual Object Detection in Streaming Video

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Abstract

Humans can watch a continuous video stream and effortlessly perform continual acquisition and transfer of new knowledge with minimal supervision yet retaining previously learnt experiences. In contrast, existing continual learning (CL) methods require fully annotated labels to effectively learn from individual frames in a video stream. Here, we examine a more realistic and challenging problem—Label-Efficient Online Continual Object Detection (LEOCOD) in streaming video. We propose a plug-and-play module, Efficient-CLS, that can be easily inserted into and consistently improve existing CL algorithms for object detection in video streams with reduced data annotation costs and model retraining time. We show that our method has achieved significant improvement with minimal forgetting across all supervision levels on two challenging CL benchmarks for streaming real-world videos. Remarkably, with only 25% annotated video frames, our proposed method still outperforms the state-of-the-art CL models trained with 100% annotations on all video frames. The data and source code will be publicly available at https://github.com/showlab/Efficient-CLS.

1. Introduction

Humans have the ability to continuously learn from an ever-changing environment, while retaining previously learnt experiences. In contrast to human learning, prior works [3, 2, 11, 34, 7] show that deep neural networks are prone to catastrophic forgetting. To address the forgetting problem, existing works in continual learning (CL) primarily focus on class-incremental image classification or object detection. Their experiment settings are often idealistic and simplified, where *i.i.d. static images* are usually grouped by class and incrementally presented to computational models in sequence. To learn a particular task containing specific classes, an agent can go through all the data of current task *over multiple epochs*. After that, the learned classes in current task become unavailable, *i.e.*, *no overlaps* between the sets of learned classes and unseen classes.

However, these experiment designs deviate from the online continual learning (OCL) setting in the real world, where an agent learns from *temporally correlated non-i.i.d. video streams in one single pass*. Given context regularities in natural environments, an agent is likely to encounter cases when objects of previously learnt classes *co-occur* with unknown objects from unseen classes, *e.g.*, a computer mouse and a computer monitor often co-occur. Taking these considerations, [34] introduces OCL on object detection in real-world video streams. They evaluate existing CL approaches on this setting and report a huge performance gap compared with offline training.

Based on the setting in [34], we take a significant step further and introduce a novel problem setting called Label-Efficient Online Continual Object Detection (LEOCOD), which highlights two unique challenges. First, the setting in [34] is such that the CL algorithms are trained with every mini-batch over multiple passes. We tighten the training recipe in LEOCOD to strictly online, where data is allowed to have one single pass and models are trained on the entire video dataset for only one epoch. Second, existing CL models require fully supervised training where box-level ground truth labels of every object on every video frame have to be obtained from human annotators. Unlike static images, acquiring human annotations for object detection on videos can be expensive and daunting. Thus, in LEOCOD, the video frames per mini-batch are sparsely annotated to alleviate the burdens of extensive human labeling, making LEOCOD one step closer to real world application.

Cognitive science works [35, 19] show that humans are efficient at continuously learning from very few annotated data samples. We get inspirations from the theory of Complementary Learning Systems (CLS) in human brains [18], and propose a plug-and-play module for the LEOCOD task, dubbed as Efficient-CLS. In Efficient-CLS, we introduce

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two feed-forward neural networks as slow and fast learners. In the fast learner, memory is rapidly adapted to the current task. The weights of the slow learner change a little on each reinstatement, and are maintained by taking the exponential moving average (EMA) of the fast learner’s weights over time. Though a few continual learning models in previous works [4, 24] also use a similar source of inspiration, they miss the effect of reciprocal connections from slow learners to fast learners, which we intend to address. Inspired by the bidirectional interaction in CLS [14], we reactivate the weights of the slow learners to predict meaningful pseudo labels from the unlabeled video frames and use these pseudo labels to guide the training of the fast learner, closing the loop between the two systems.

We demonstrate the versatility and effectiveness of our Efficient-CLS on two standard real-world video datasets, OAK [34] and EgoObjects [1]. Our proposed method can be easily integrated into existing CL models and consistently improve their performance by a large margin in LEOCOD. It is worth noting that, with only 25% labeled data, our method surpasses the comparative baselines trained with full supervision (Figure 1(b)).

To summarize, we make the following key contributions:

- We introduce a new, challenging and important problem of label-efficient online continual object detection (LEOCOD) in video streams. Solving this problem would greatly benefit real-world applications in reducing annotation cost and model retraining time.

- We propose Efficient-CLS, a plug-and-play module inspired from the Complementary Learning Systems (CLS) theory, which can be integrated into existing CL models and learn efficiently and effectively with less supervision and minimal forgetting.

- We benchmark existing CL methods on the task of LEOCOD and demonstrate the state-of-the-art performance of our method through extensive experiments.

2. Related Work

2.1. Continual Learning

To alleviate catastrophic forgetting, many continual learning methods exploit an external buffer where a limited number of old samples are stored and used for replay when adapting to a new task. iCaRL [26] stores the representative exemplars in past tasks for knowledge distillation and prototype rehearsal. Gradient Episodic Memory (GEM) [21] formulates optimization constraints on the exemplars in memory. Averaged GEM (A-GEM) [8] is an improved version of GEM that achieves faster training and less memory consumption. GDumb [25] greedily stores samples in memory as they come and trains a model using samples only in the memory. Dark Experience Replay++ (DER++) [6] combines replay with knowledge distillation and regularization, and samples logits along the entire optimization trajectory.

In contrast to classical continual learning where data are separated by task boundaries and models are trained with multiple iterations in every task, we examine a more realistic and challenging problem where data are provided in tiny batches and models are trained on these batches only once. Recently, online continual learning (OCL) has gained increasing interests in computer vision [3, 7, 29, 9, 34]. Many OCL methods rely on representative memory replays to pre-
vent forgetting. [3] utilizes gradients of network parameters to select replay samples of maximum diversity. Subsequent works [2, 29] propose to use losses and scoring functions as criteria for selecting the most representative samples for replay. However, these approaches tackle image classification problems in an artificial setting, where new classes appear in a specific order. Their performance in real-world vision tasks remains unclear.

Lately, [34] benchmarks CL methods in the real-world online setting with full supervision. As the video streams arrive endlessly in a real-time manner, assigning annotations to all the video frames for training computational models is laborious and time-consuming. It becomes even more daunting in object detection tasks where class labels and bounding boxes of all objects on a video frame have to be provided. Reducing burdensome costs of labeling remains an under-explored and challenging problem in online continual object detection. We propose a self-sustaining Efficient-CLS, which is capable of exploiting the unlabeled video frames by pseudo-labeling when the number of labeled frames is limited.

2.2. Complementary Learning Systems

The essence of fast and slow learning in Complementary Learning Systems (CLS) has benefited several continual learning algorithms in image recognition [24, 23, 28, 4, 15]. However, these methods either require the task boundaries, which are not applicable in our online video setting, or they require to train fast and slow learning systems with replay samples from the same replay buffer, which could easily lead to overfitting problem when the replay buffer has limited capacity. To eliminate overfitting problem, [28] and [15] utilize generative replay models to couple sequential tasks in a latent embedding space. While generative approaches have succeeded in artificial and simple datasets, they often fail in complex vision tasks, e.g., object detection. DualNet [23] also employs a slow-fast learning architecture. However, its update process for the slow learner is more computationally demanding because it leans on both self-supervised and supervised learning objectives. The self-supervised phase demands additional training iterations on extensive batches to yield satisfactory results, thereby delaying the training of the fast learner. In contrast, our method updates the slow learner in real-time using the fast learner’s weights, obviating the need for distinct slow learner training. Our approach is optimized for online CL scenarios where computational resources are constrained.

2.3. Semi-Supervised Learning

The goal of semi-supervised learning (SSL) [33, 5, 37, 36] is to reduce the demand of labeled data and harness unlabeled data for performance improvement. [31] first introduce SSL to the context of CL, and propose a strategy that combines pseudo-labeling, consistency regularization, out-of-distribution detection, and knowledge distillation to solve the problem of class-incremental image classification. However, to distill knowledge from previous tasks, their model relies heavily on the task boundary that identifies the change of training classes, which is not available in our LEOCOD setting. To reduce annotation costs in object detection, several methods [13, 32, 20] capitalize the teacher-student networks. In general, a teacher model predicts pseudo labels or enforces a consistency loss to guide the student networks. However, these previous works on semi-supervised object detection only consider the offline setting on static image datasets, while none of them has been extended to online continual learning on dynamic video streams. We discovered new insights that pseudo-labeling from slow learner to fast learner can not only reduce annotation overhead, but also alleviate forgetting, which is critical to the design of efficient continual learners in real world.

3. Method

3.1. Problem Setting

We advance the online continual object detection in [34] to a label-efficient and computationally-efficient setting—Label-Efficient Online Continual Object Detection (LEOCOD). In contrast to the setting in [34] where video frames are extensively annotated and trained with multiple epochs, an agent in LEOCOD continuously learns from a sparsely annotated video stream in a single pass over time (see Figure 1(a)).

Formally, we consider the online continual object detection on a continuum of video streams \( D = \{ D_1, \cdots, D_T \} \), where at time step \( t \), a learning agent receives a mini-batch of continuous video frames \( D_t \) from current environment for online training (one single pass). To perform label-efficient object detection, within the batch \( D_t \), only a subset of video frames \( D^s_t = (X^s_t, Y^s_t) \) are labeled, while the remaining video frames \( D^u_t = (X^u_t) \) are unlabeled. For each labeled data sample, its annotation contains the bounding box locations and their corresponding class labels.

3.2. Efficient Complementary Learning Systems

We propose a plug-and-play module dubbed as Efficient-CLS. Specifically, it consists of two feed-forward networks: (i) the fast learner is designed to quickly encode new knowledge from current data stream and then consolidate it to the slow learner; and (ii) the slow learner accumulates the acquired knowledge from fast learner over time and guides the fast learner with meaningful pseudo labels, when full supervision is not available. Same as [26, 8, 25, 6, 34], we maintain an external episodic memory, as a replay buffer, to store exemplars that can be retrieved for replays alongside ongoing video stream. As the fast and slow learners are
model agnostic, our Efficient-CLS can be easily integrated into existing CL models, which leads to less supervision and minimal forgetting.

**Learning with Labeled Frames.** The fast learner and slow learner use the same standard Faster-RCNN [27] detector \( f \). Despite the same architecture, the weights of the fast and slow learners are not shared. We use \( \theta_f \) and \( \theta_s \) to denote the network parameters for fast and slow learners respectively. As shown in Figure 2, at each training step \( t \), we use the labeled video frames \( D^t_s = (X^t_s, Y^t_s) \) to optimize the fast learner \( \theta_f \) with the standard supervised loss \( L_{\text{sup}} \) in Faster-RCNN [27]. It consists of four losses: Region Proposal Network (RPN) classification loss \( L_{\text{rpn}}^{\text{cls}} \), RPN regression loss \( L_{\text{rpn}}^{\text{reg}} \), Region of Interest (ROI) classification loss \( L_{\text{roi}}^{\text{cls}} \), and ROI regression loss \( L_{\text{roi}}^{\text{reg}} \). We define \( L_{\text{sup}} \) as:

\[
L_{\text{sup}} = L_{\text{cls}}^{\text{rpn}}(X^t_s, Y^t_s) + L_{\text{reg}}^{\text{rpn}}(X^t_s, Y^t_s) + \\
L_{\text{cls}}^{\text{roi}}(X^t_s, Y^t_s) + L_{\text{reg}}^{\text{roi}}(X^t_s, Y^t_s).
\]

**Learning with Unlabeled Frames.** We introduce a pseudo-labeling paradigm to capitalize the information from unlabeled video frames \( D^t_u = (X^t_u) \) for training. In our early exploration, we intuitively use the fast learner for pseudo-labeling as it quickly adapts the knowledge of nearby frames. However, we observe that using the pseudo labels generated by the fast learner for self-replay exhibits biases towards recently seen objects, which is less effective in preventing forgetting. This has also been verified in our ablation study (Section 5.3). In contrast, the slow learner preserves the semantic knowledge over a longer time span which generates pseudo labels with fewer biases. This encourages the fast learner to capture more generic scene representations, hence, in turn, contributing to reinstatement of memory in the slow learner (Section 3.2), resulting in a positive feedback loop.

Given all these design considerations, the slow learner takes the unlabeled video frames \( D^t_u \) as inputs to estimate the possible objects of interest and their corresponding bounding box locations. For brevity, we refer these “pseudo bounding boxes and their corresponding class labels” as “pseudo labels” in the paper. To get rid of false positives, we apply a threshold \( \tau \) to filter out bounding boxes with predicted low confidence scores. Moreover, there also exist repetitive boxes which negatively impact the quality of pseudo-labeling. To address this issue, we use the technique of class-wise non-maximum suppression (NMS) [27] to remove the overlapped boxes and get the high-quality pseudo labels. Formally, the procedure of pseudo label generation is summarized below:

\[
Y^t_u = \text{NMS}([f(X^t_u; \theta_S)]_{>\tau}),
\]

where \([\cdot]_{>\tau}\) denotes the bounding box selection with confidence score larger than \( \tau \).

Given that the video streams are captured from the egocentric perspective in the real world, head and body motions may lead to undesired motion blur effects on some video frames. To enforce our module to learn invariant object representations from these video frames, same as the previous work [38], we apply data augmentation techniques on the pseudo-labeled frames, including 2D image...
crops, rotations, and flipping. Note that different from image classification, the predicted bounding box locations also need to be updated accordingly after image augmentations. We denote these pseudo-labeled video frames and their re-adjusted pseudo labels after data augmentations as \((\tilde{X}_t^n, \tilde{Y}_t^n)\). We can then use these pseudo pairs \((\tilde{X}_t^n, \tilde{Y}_t^n)\) to train the fast learner by optimizing the pseudo loss \(L_{\text{pseudo}} := L_{\text{cls}}(\tilde{X}_t^n, \tilde{Y}_t^n) + L_{\text{reg}}(\tilde{X}_t^n, \tilde{Y}_t^n)\).

Overall, our Efficient-CLS is jointly trained with the following losses: \(L_{\text{total}} = L_{\text{sup}} + \lambda_{\text{pseudo}} L_{\text{pseudo}}\), where \(\lambda_{\text{pseudo}}\) is the weight of \(L_{\text{pseudo}}\).

**Synapses Consolidation via EMA.** To alleviate forgetting of obtained knowledge, we apply Exponential Moving Average (EMA) to gradually update the slow learner with the fast learner’s weights. The evolving weight changes in the slow learner are functionally correlated with the memory consolidation mechanism in the hippocampus and the neocortex [4]. Formally, we define EMA process as:

\[
\theta_S = \alpha \theta_S + (1 - \alpha) \theta_F,
\]

where the \(\alpha \in [0, 1]\) is EMA rate. According to the stability-plasticity dilemma, a smaller \(\alpha\) means faster adaptation but less memorization. Empirically, we set \(\alpha = 0.99\), which leads to best performance.

4. Experimental details

4.1. Datasets

We evaluate the continual learning methods on two realistic and challenging video datasets, OAK [34] and EgoObjects [1], for the task of online continual object detection.

**OAK** [34] is a large egocentric video stream dataset spanning nine months of a graduate student’s life, consisting of 7.6 million frames of 460 video clips with a total length of 70.2 hours [30]. The dataset contains 103 object categories. We follow [34] in the ordering of training and testing data splits. One frame every 16 consecutive video frames lasting for 30 seconds is held out to construct a test set and the remaining frames are used for training.

**EgoObjects** [1] is one of the largest object-centric datasets focusing on object detection task. The dataset contains around 100k video frames with \(~250k\) annotations, which correspond to 277 categories and 1110 main objects [22]. Additionally, the dataset follows a long-tailed distribution which makes the task more challenging and real-world oriented. We adopt the same rule as OAK dataset to split the training and testing set.

4.2. Baselines

We compare our model against the following baselines: 1) **Vanilla training**: Incremental Training is a naive baseline trained sequentially over the entire video stream without any measures to avoid catastrophic forgetting; **Offline Training** is an upper bound that can access all the data throughout training; 2) **Continual learning algorithms**: EWC [16], iCaRL [26], A-GEM [8], GDumb [25], DER++ [6] and iOD [17].

The iCaRL model implemented by [34] stands as the SOTA method in online continual object detection. We reproduce their results using the released code\(^1\). When calculating RPN and ROI losses for replay samples, their iCaRL model neglects the losses of background proposals and penalizes the foreground losses according to the proportion of the current samples and replay samples. We empirically found that this trick hinders the model from effective episodic replay, thus resulting in severe forgetting. Therefore, we re-implement the iCaRL by discarding the re-weighting trick and reverting back to the standard RPN and ROI losses. We name these two different implementations as iCaRL(Wang et al.) and iCaRL(our impl.), respectively.

4.3. Evaluation

**Protocols.** First, we define the annotation cost as the proportion of number of labeled frames versus the total 16 frames within a mini-batch \(D_t\). For example, if 2 out of 16 consecutive frames within \(D_t\) get labeled, the annotation cost is \(2/16 = 12.5\%\). The frames to be labeled are randomly selected within each mini-batch \(D_t\). Considering that different choices of labeled frames might influence the model performance, for fair comparisons between models, we fix the choice of randomly selected labeled frames and use the same labeled and unlabeled frames for training all models. Based on the various annotation costs, we introduce two training protocols: fully supervised protocol (100\% annotation cost) and sparse annotation protocol (where the annotation cost is less than 100\%). In sparse annotation protocol, we further split the training experiments based on 50\%/25%/12.5%/6.25\% annotation costs.

**Metrics.** We evaluate the models with three standard metrics: continual average precision (CAP), final average precision (FAP) and forgetfulness (F) [34]. We employ an Average Precision (AP) metric at an Intersection over Union (IoU) threshold of 0.5, commonly referred to as AP50.

**CAP** shows the average performance over the entire video stream. That is,

\[
\text{CAP} = \frac{1}{N} \sum_{i=0}^{N} \text{CAP}_{t_i} = \frac{1}{NC} \sum_{i=0}^{N} \sum_{c=0}^{C} \text{CAP}_{t_i}^c,
\]

where \(\text{CAP}_{t_i}^c\) is the AP of class \(c\) on test set at the \(i\)-th evaluation step, \(N\) is the total number of evaluation steps.

**FAP** is the final performance of a model after seeing the entire video. That is, \(\text{FAP} = \text{CAP}_{t_N}\), where \(t_N\) denotes the last evaluation step.

\(^1\)https://github.com/oakdata/benchmark
iments were conducted on 2 NVIDIA RTX 3090 GPUs. The weight of pseudo loss $\lambda$ performance decrease at each time:

The overall forgetfulness is:

$$F = \sum_{c=0}^{C} F_c.$$  

(5)

The overall forgetfulness is:

$$F = \frac{1}{C} \sum_{c=0}^{C} F_c.$$  

4.4. Implementation Details

For a fair comparison, we followed the prior work [34] to use Faster-RCNN [27] with ResNet-50 backbone [12] as our object detection network, which is initialized by the weights pre-trained on PASCAL VOC [10]. We used Adam optimizer with a constant learning rate of 0.0001, and the batch size was set to 16 frames. Same as [34], we maintained a replay buffer with 5 samples per class. At each time step $t$, we first randomly retrieved 16 video frames from the replay buffer for joint training. We used confidence threshold $\tau = 0.7$ to generate pseudo-labels for unlabeled frames, and applied EMA rate $\alpha = 0.99$ to update the slow learner. The weight of pseudo loss $\lambda_{pseudo}$ was set to 1.0. All the experiments were conducted on 2 NVIDIA RTX 3090 GPUs.

5. Results

5.1. Fully Supervised Protocol

As the previous work [34] focuses on online continual object detection (OCOD) in video streams, we first evaluated model performance in fully supervised setting (i.e., 100% annotation cost), where all video frames are paired with human labels. The reported results were measured by standard metrics (CAP, FAP, and F, Section 4.3) in Table 1.

<table>
<thead>
<tr>
<th>Method</th>
<th>Annotation Cost</th>
<th>OAK</th>
<th>EgoObjects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>FAP (%)</td>
<td>CAP (%)</td>
</tr>
<tr>
<td>Incremental</td>
<td>100%</td>
<td>8.38</td>
<td>7.72</td>
</tr>
<tr>
<td>Offline Training</td>
<td>100%</td>
<td>48.28</td>
<td>35.23</td>
</tr>
<tr>
<td>EWC</td>
<td>100%</td>
<td>7.73</td>
<td>7.02</td>
</tr>
<tr>
<td>iOD</td>
<td>100%</td>
<td>7.92</td>
<td>7.14</td>
</tr>
<tr>
<td>iCaRL(Wang et al.)</td>
<td>100%</td>
<td>22.89</td>
<td>16.60</td>
</tr>
<tr>
<td>iCaRL(our impl.)</td>
<td>100%</td>
<td>36.14</td>
<td>26.26</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>25%</td>
<td>38.36 (+2.22)</td>
<td>26.64 (+0.38)</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>100%</td>
<td>40.24 (+4.10)</td>
<td>28.18 (+1.92)</td>
</tr>
<tr>
<td>A-GEM</td>
<td>100%</td>
<td>36.94</td>
<td>26.19</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>25%</td>
<td>37.06 (+0.12)</td>
<td>26.36 (+0.17)</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>100%</td>
<td>39.87 (+2.93)</td>
<td>27.97 (+1.78)</td>
</tr>
<tr>
<td>GDumb</td>
<td>100%</td>
<td>35.27</td>
<td>25.29</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>25%</td>
<td>37.67 (+2.40)</td>
<td>25.59 (+0.30)</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>100%</td>
<td>38.61 (+3.34)</td>
<td>26.04 (+0.75)</td>
</tr>
<tr>
<td>DER++</td>
<td>100%</td>
<td>37.79</td>
<td>25.24</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>25%</td>
<td>37.93 (+0.14)</td>
<td>25.64 (+0.4)</td>
</tr>
<tr>
<td>w/ Efficient-CLS</td>
<td>100%</td>
<td>39.61 (+1.82)</td>
<td>26.73 (+1.49)</td>
</tr>
</tbody>
</table>

Table 1. Overall performance of existing algorithms and Efficient-CLS on OAK and EgoObjects. iCaRL(Wang et al.) denotes the SOTA model presented in [34], and iCaRL(our impl.) is the same method by our implementation.

Performance of CL baselines. [34] benchmarked Incremental, EWC, iCaRL(Wang et al.), and Offline Training on OAK dataset. They found the replay-based method (i.e., iCaRL(Wang et al.)) outperforms regularization-based method (i.e., EWC) by 10% in FAP, while iCaRL(Wang et al.) has a huge gap of 30% compared with Offline Training. Similar observations were made in Table 1, but the performance of Incremental and EWC were 4% lower than that in [34], as in our setting we only trained each mini-batch of video frames once (they trained each mini-batch 10 times).

As mentioned in Section 4.2, we introduce several variations to the original design of iCaRL(Wang et al.). Compared with iCaRL(Wang et al.), we observed a huge performance boost in FAP from 22.89% to 36.14% on OAK and from 37.61% to 60.80% on EgoObjects, abridging the gap between the baseline and Offline Training.

We further adapted other standard CL baselines, including iOD, A-GEM, GDumb, DER++, to the OCOD setting for comparisons. iOD is the SOTA method in offline class-incremental object detection. Though it performs well in prior setting, iOD collapses when adapted to online video streams. One explanation is that iOD requires explicit task boundary to trigger the reshape of model gradients that opti-
mizes knowledge sharing between adjacent tasks. However, in online video streams, the task boundaries by classes are no longer available and the change of tasks is hard to identify, resulting in the failure to prevent forgetting. In contrast, replay-based methods (i.e., A-GEM, GDumb and DER++) generalize much better to the real-world streaming video.

**Performance w/ Efficient-CLS.** Inheriting from the benefit of fast and slow learning with EMA, our Efficient-CLS consistently improves all the state-of-the-art CL methods (i.e., iCaRL(our impl.), A-GEM, GDumb and DER++) by a significant margin. Taking iCaRL(our impl.) for example, with Efficient-CLS, we observed superior performance and minimal forgetting compared to baseline methods, even when categories appeared infrequently (e.g., sculpture in Figure 3). Since semantic contextual information is more important in indoor environments on EgoObjects compared to the outdoor environments in OAK, we noticed that the improvement brought by our method is even greater on EgoObjects with an increase of 6.25% in FAP, 3.95% in CAP % and 3.07% in F. Consistent performance gains are also noticeable for A-GEM, GDumb and DER++, demonstrating the effectiveness and flexibility of our method.

### 5.2. Sparse Annotation Protocol

**Performance of CL baselines.** The sparse annotation protocol is more challenging than the previously supervised protocol as shown by the performance differences when number of annotated video frames decreases (compare the performance of each colored bar along the x-axis within each subplot in Figure 4). We noted that GDumb is more resilient against the reduce of supervision. Specifically, from Table 2 at the lowest annotation cost of 6.25% on EgoObjects dataset, GDumb achieves the highest performance of 38.74%, 22.69% and -4.53% in FAP, CAP and F, which surpasses other baselines by a considerable margin. Some observations can be made on OAK dataset. One possible explanation is that GDumb only trains the data stored in the balanced replay buffer, which makes it less vulnerable to class imbalance problem brought by the reduce of labeled samples in the training set.

**Performance w/ Efficient-CLS.** Our proposed Efficient-CLS is a plug-and-play module that can be easily inserted into and enhance existing continual learning algorithms with the ability to use unlabeled video frames effectively. In both OAK and EgoObjects dataset, Efficient-CLS consistently improves the comparative SOTAs in all three evaluation metrics regardless of various degrees of annotation cost. As shown in Table 2, at a lower annotation cost of 6.25%, Efficient-CLS doubles the performance of DER++ and A-GEM in terms of FAP and CAP, and achieves an even larger improvement in preventing forgetting. Thanks to the useful information from pseudo labels predicted by the slow learner in Efficient-CLS, our method is more robust to various annotation costs, compared with SOTAs (compare the rate of change of blue bars vs. red bars over different degrees of annotation cost). Most remarkably, Efficient-CLS with 25% annotation cost has already outperformed comparative SOTAs with 100% annotation cost (see Table 1).

### 5.3. Ablation Study

We assessed the importance of our key design choices. The Complementary Learning Systems (CLS) in Efficient-CLS is the key for rapidly adapting to learn new tasks, meanwhile, retaining previously learnt knowledge. It constitutes of two memory reinstatement mechanisms: one is
Figure 4. Evaluation of online continual object detection in video streams with three metrics (FAP, CAP and F, Section 4.3) on OAK dataset (first row) and EgoObjects dataset (second row). The higher the bars are, the better. The x-axis denotes the percentage of video frames that are labeled in the video stream. It ranges from 6.25% to 100% (full supervision). The y-axis indicates the performance using different evaluation metrics. Ours (iCaRL(our impl.) w/ Efficient-CLS, red) consistently beats the comparative SOTA (iCaRL(our impl.), blue) in all evaluation metrics.

Table 3. Effectiveness of Exponential Moving Average (EMA) and Pseudo-labeling (PL) for iCaRL(our impl.) on OAK dataset at annotation cost 50%, 25%, 12.5% and 6.25%. The best results are bold-faced.

<table>
<thead>
<tr>
<th>EMA</th>
<th>PL</th>
<th>50% FAP</th>
<th>50% CAP</th>
<th>50% F</th>
<th>25% FAP</th>
<th>25% CAP</th>
<th>25% F</th>
<th>12.5% FAP</th>
<th>12.5% CAP</th>
<th>12.5% F</th>
<th>6.25% FAP</th>
<th>6.25% CAP</th>
<th>6.25% F</th>
</tr>
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synaptic weight transfer from fast to slow learner via exponential moving average (EMA); and the other is reciprocal replay from slow learner to fast learner with pseudo-labeling (PL). Here we studied their effects individually.

Ablation: Exponential Moving Average (EMA). We removed EMA by setting the \( \alpha \) in Equation 3 to 1, where the model weights of the fast learner and slow learner are now shared throughout the learning process. Note that in the fully supervised protocol, the pseudo-labeling is turned off and the Efficient-CLS equals to the EMA alone. From Table 1 at 100% annotation cost, we observed that removing EMA leads to significant performance drops ranging from 2% to 8%, for all the comparative baselines on both OAK and EgoObjects. This shows that the slow learner can effectively consolidate the knowledge from the fast learner, and constructively alleviate catastrophic forgetting by synapses consolidation over time. Similar observations were made in Table 3 in the sparse annotation protocol (compare Row 2 vs. Row 1, Row 4 vs. Row 3). It is worth noting that, the performance difference between naive model (Row 1) and its variant with EMA (Row 2) is slightly larger in lower supervision (i.e. 12.5%, 6.25%) than higher supervision (i.e. 50%, 25%). One possible reason is that, compared with higher supervision, the fast learner suffers more forgetting in lower supervision; hence, the effect of removing EMA becomes stronger in lower supervision, again highlighting the importance of EMA.

Ablation: Pseudo-labeling (PL). We ablate our model by removing the PL of the slow learner across varying annotation costs and reported the results in Table 3. The removal of PL (Row 2) leads to a performance drop of around 2% in FAP, 1% in CAP and 0.5-4% in F, compared with our full Efficient-CLS (Row 4). It implies that the slow learner captures useful semantic information from unlabeled video frames and these predicted pseudo labels are helpful in training the fast learner.

To investigate whether pseudo-labels predicted by the fast learner itself could help stream learning, we conducted another ablation experiment where we performed PL without EMA (Row 3). Compared with the naive model (Row 1), we observed a performance increase from 28.76% to 31.60% in FAP and 19.80% to 22.44% in CAP. It indicates...
that, due to the temporal correlation in video stream, pseudo labels predicted by the fast learner can serve as an informative supervision for the training of the fast learner itself.

However, replaying the self-predicted pseudo labels on the fast learner fails to prevent forgetting, as indicated by the drop from -5.48% to -4.83% in F. It is possible that the pseudo labels generated by the fast learner only bias towards the classes which have already been learnt very well and fail to reinforce the fast learner to improve on the poorly-learnt classes. Different from the fast learner, the slow learner integrates semantic information over time. The predicted pseudo labels carry more semantic information, which is useful for fast learner to capture more generic object representations during pseudo label replays. Again, this emphasizes that the reciprocal replay from the slow learner to the fast learner is critical for memory reinstatement, which has been missing in the computational modeling literature of CLS.

6. Conclusion

To imitate what humans see and learn in the real world, we introduce a more realistic and challenging problem of label-efficient online continual object detection (LEOCOD) in video streams. Addressing this problem would greatly benefit real-world applications by reducing model retraining time and data labeling costs. Inspired by the Complementary Learning Systems (CLS) theory, we propose a plug-and-play module, namely Efficient-CLS, that can be easily integrated into and improve existing continual learning algorithms. We evaluate Efficient-CLS on two challenging real-world video datasets, where our method achieves the state-of-the-art performance in preventing catastrophic forgetting, all while requiring minimal annotation effort.

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References


