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Challenges in Task Incremental Learning for Assistive Robotics

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ABSTRACT Recent breakthroughs in computer vision areas, ranging from detection, segmentation, to classification, rely on the availability of large-scale representative training datasets. Yet, robotic vision poses new challenges towards applying visual algorithms developed from these datasets because the latter implicitly assume a fixed set of categories and time-invariant distribution of tasks. In practice, assistive robots should be able to operate in dynamic environments with everyday changes. The variations of four commonly observed factors, including illumination, occlusion, camera-object distance/angles and clutter, could make lifelong/continual learning in computer vision more challenging. Large-scale datasets previously made publicly available were relatively simple, and rarely include such real-world challenges in data collection. Benefited from the recent released OpenLORIS-Object dataset, which explicitly includes these real-world challenges in the lifelong object recognition task, we evaluate three most adopted regularization methods in lifelong/continual learning (Learning without Forgetting, Elastic Weights Consolidation, and Synaptic Intelligence). Their performances were compared with the naive and cumulative training modes as the lower bound and upper bound of performances, respectively. The experiments conducted on the dataset focused on task incremental learning, i.e., incremental difficulty based on the four environment of factors. However, all the three most reported lifelong/continual learning algorithms have failed with the increase in encountered batches across various metrics with indistinguishable performance comparing to the naive training mode. Our results highlight the current challenges in lifelong object recognition for assistive robots to operate in real-world dynamic scene.

INDEX TERMS Machine intelligence, robotic vision systems.

I. INTRODUCTION

Humans are capable of accumulating new knowledge without retaining complete learned information. This process is known as lifelong/continual learning. Yet, it is challenging for robots to retain earlier knowledge when they encounter new tasks or information. The ability of lifelong/continual learning is, however, essential in particular to assistive robotics for elderlies or patients with disabilities [1], [2]. The quality of control input of assistive robotics is dependent on the subject condition and can vary across time and environment [3], [4]. Here, for facing with the varying environments and conditions, lifelong/continual robotics vision will help to operate with such nonstationary human control inputs.

Latest advances in computer vision performance were initially driven by the availability of large-scale datasets, such as ImageNet and COCO, for training and the more powerful computational hardware [5], [6]. However, robotic vision poses new challenges for applying visual algorithms developed from these computer vision datasets because they implicitly assume a fixed set of categories and time-invariant task distributions. Semantic concepts change dynamically over time. Thus, sizeable robotic vision datasets collected from real-time changing environments for accelerating the research and evaluation of robotic vision algorithms are crucial.

In real-world scenarios, assistive robotics has to be able to operate under an open environment with uncertainties continuously. Some commonly observed factors, such as illumination, occlusion, the angle/distance between

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the camera and objects (leading to different pixel sizes of objects in the images), and clutter, could already make lifelong/continual learning in computer vision more challenging. The lifelong/continual learning capability of assistive robotic systems to provide reliable estimates in environments with such uncertainties requires robust algorithm design. Object recognition plays a vital role in assistive robotics applications since visual recognition functions are crucial for assistive robots to make decisions and plan their actions, such as visual-based robotic grasping and manipulation. Thus in this context, the lifelong object recognition is a fundamental problem.

Lifelong object recognition problems were previously defined as: 1) instance-incremental; 2) class-incremental; and/or 3) attribute-incremental [7]. It is essential to test the ability of the algorithm to learn continuously without forgetting the previously learned patterns in terms of the instance, class, and/or attribute. The challenge is to explore how to utilize the knowledge gained from previous tasks that can help to better learn new tasks and how to effectively remember tasks that have been learned before. In other words, ideal assistive robots shall behave like humans with the ability to transfer, associate, and combine the knowledge. Thus far, Learning without Forgetting (LwF), Elastic Weights Consolidation (EWC), and Synaptic Intelligence (SI) are three widely-studied lifelong/continual learning methods applied to class and instance incremental learning[1] [10]–[12]. Their performance to variations in environmental factors, yet, remain unknown. Therefore, in this work, we look into the performance of these state-of-the-art methods on recordings with different illumination, occlusion, the angle/distance between the camera and objects (finally lead to different pixel size in the image) and clutter to shed light on their limitations in practice.

II. METHODS

A. TASK INCREMENTAL SCENARIOS FOR ASSISTIVE ROBOTS

The setting of task incremental learning is crucial to the stability and plasticity of task incremental learning for assistive robots. Here, we have defined task incremental as incremental on the difficulty for robots to recognize the object based on four common factors, which describe different environments the robots encountered with. The factors include illumination, occlusion, the angle/distance between the camera and objects, and clutter. Here, we listed three difficulty levels for each environmental factor, as shown in Table 1.

This categorization includes these three difficulty degree data and guaranteed the other three factors fixed on difficulty degree 1 when one factor's difficulty varied. We have studied the performance for different difficulty degrees when one of all factors was changed respectively. The data was

[1]There are some other Lifelong/Continual Learning algorithms, such as Deep Generative Replay [8] and Variational Continual Learning [9], and we pick these three representative methods in the paper because they are mature and their original results are relatively easy to be reproduced.

TABLE 1. Task difficulty degrees of four environment factors.

	Illumination	Occlusion	Pixel Size	Clutter
Degree 1	Strong	0%	$> 200 \times 200$	Low
Degree 2	Normal	25%	$30 \times 30 - 200 \times 200$	Normal
Degree 3	Weak	50%	$< 30 \times 30$	High

collected in real scenes, similar to those in real-world assistive robot operation when the robots had to perform robustly in a dynamic environment. The details of our data collection, annotation, and experimental design were described in [13], [14]. The dataset collected home and office objects in dynamic environments such as office room, living room, and kitchen. The sensor collected different videos of objects under multiple factors, including illuminations, occlusions, camera-object distances/angles (pixel sizes), and context information (clutters). For each individual factor, the dataset contains three different difficulty levels. The overview of the dataset is shown as Figure 1, with 6 objects randomly selected and factors' level variations.

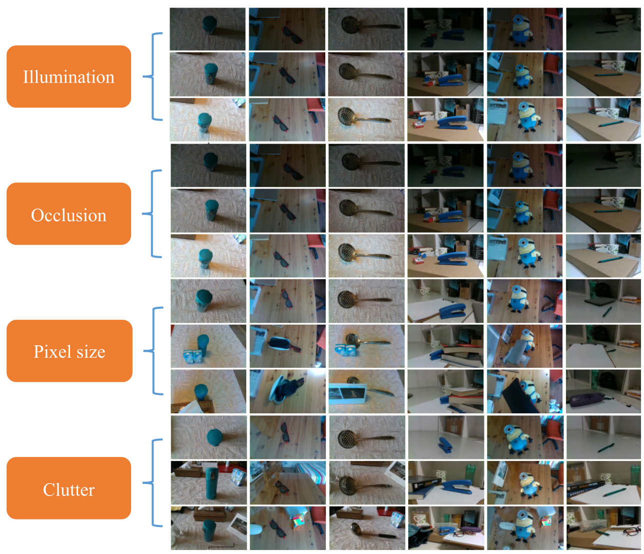

FIGURE 1. OpenLORIS-Object Dataset [13] Overview: showing four challenges (illumination, occlusion, object pixel size, and clutter) with three-level variants, picked samples of 6 objects (cup, glass, ladle, stapler, toy and pencil) being presented.

B. LIFELONG/CONTINUAL LEARNING METHODS

Most recent computer vision methods have been established on deep neural networks, which have a fundamental issue called catastrophic forgetting that has not been addressed yet [15]. It can lead to the decreasing performance for learning systems when new knowledge interferes with previously trained knowledge [16], [17]. Many strategies have been proposed in recent years in order to overcome catastrophic forgetting in the field of lifelong learning [18]–[20]. However, due to the experimental setting in previous research, very few implemented their state-of-the-art methods on task incremental learning protocols [7]. Here, we have implemented Elastic Weights Consolidation (EWC), Synaptic Intelligence (SI), and Learning without Forgetting (LwF) on our task incremental learning dataset [10]–[12].

1) ELASTIC WEIGHTS CONSOLIDATION AND SYNAPTIC INTELLIGENCE

Elastic Weights Consolidation (EWC) and Synaptic Intelligence (SI) have proposed quantitative ways to estimate the importance of each parameter to the final target function of lifelong learning tasks by measuring the output of previous tasks. In other words, both methods utilize a representation and computation to compute the importance of parameters' importance level. Such importance level measurement is calculated by some regularization representation. Thus, when a new task is trained, the network regularizes the backbone network's parameters by giving penalties for changes in some parameters. For those parameters which illustrated high importance level for previous tasks will be protected from changing significantly. Both of these two methods implement this intuitive idea by defining surrogate loss function with penalties. The loss functions of these two methods are given by Equation 1.The differences of them are how they regularize the network parameters. Besides using current tasks' loss to learn current information, EWC uses the fisher information to calculate the sensitiveness of each parameter for the likelihood function. SI reflects past credit for improvements of the current task objective to individual parameter with surrogated loss.

$$\widetilde{\mathcal{L}}_{EWC/SI} = \underbrace{\mathcal{L}_{new}}_{\text{current tasks' loss}} + \underbrace{\lambda_{EWC/SI} \sum_{i=1}^{l} \Omega(\theta_n^{(i)} - \theta_o^{(i)})^2}_{\text{surrogate loss}} \quad (1)$$

where $\widetilde{\mathcal{L}}$, $\mathcal{L}_{new}$ denotes the whole loss function and current task's loss respectively. Note that the loss function consists of two components: current loss $\mathcal{L}_{new}$ and surrogate loss. In the surrogate loss, $\lambda_{EWC/SI}$ denotes strength parameter in EWC and SI methods (λ_{EWC} in EWC method and λ_{SI} in SI method), which can be seen as hyper-parameters to control the degree of remembering previous knowledge. Ω here is to calculate the representation in previous tasks' parameters. In EWC, Ω was estimated by Fisher Information Matrix while in SI it was replaced by the curvature near extreme points [10], [11]. $\theta_n^{(i)}$ and $\theta_o^{(i)}$ are i^{th} learnt weights from current and previous tasks respectively [10], [11].

In our task incremental scenarios, we have implemented EWC and SI methods across different difficulty tasks. Although the difficulties keep varying during the learning process, some previously trained patterns are generally kept fixed and shared across multiple tasks, which means a more generalized and robust model can be learned during the lifelong learning process.

2) LEARNING WITHOUT FORGETTING

Learning without Forgetting (LwF) is also one of the state-of-the-art lifelong/continual learning methods to learn new knowledge and retain previously learned knowledge at the same time. LwF can be seen as a knowledge distillation method which only requires to access new tasks' data in lifelong/continual learning context. The distillation is modeled by using loss function to give constraints or penalties for new tasks' training. In Convolutional Neural Network (CNN) models, θ_s and θ_o denote the parameters of convolutional layers and fully connected layers in previous tasks respectively and θ_n denotes new parameters in the current task. The conventional solutions for addressing catastrophic forgetting in such CNN models are: Solution 1: keep θ_s and θ_o fixed and exploit the output of some layers in the network to train θ_n; Solution 2: optimize on θ_s, while keeping θ_o fixed and learning θ_n; Solution 3: joint training optimize θ_s, θ_o and θ_n at the same time. While Solution 1 and Solution 2 cannot always achieve high performance and Solution 3 will cost large computational burden [12].

LwF acts like a trade-off between Solution 2 and Solution 3. The pipeline of LwF contains two steps:

- Warm-up step: Renew θ_n with keeping θ_s and θ_o fixed by using new tasks' data.
- Joint-training step: Train on θ_n, θ_s and θ_o at the same time till the model converges with the distillation loss function.

Similar to EWC and SI, θ_n and θ_o can be seen as current task's and old tasks' leanrt parameters. Here the distillation loss function has two components: $\mathcal{L}_{new}$ for learning current tasks' knowledge and $\mathcal{L}_{old}$ for retaining old knowledge. The whole loss function can be formulized as Equation 2.

$$\widetilde{\mathcal{L}}_{LwF} = \lambda_{LwF} \underbrace{(-\sum_{i=1}^{l-1} y_o^{(i)} \cdot \log \hat{y}_o^{(i)})}_{\text{old tasks' loss } \mathcal{L}_{old}} \underbrace{-y_n \cdot \log \hat{y}_n + \mathcal{R}(\theta_n, \theta_o, \theta_s)}_{\text{current tasks' loss } \mathcal{L}_{new}} \quad (2)$$

where, l denotes the number of encountered tasks; y_o and $\hat{y}_n$ are ground truth and output of current task; $y_o^{(i)}$ and $\hat{y}_o^{(i)}$ represent the output of i^{th} old task computed by current task's model and ground truth of old tasks; $\mathcal{R}(\theta_n, \theta_o, \theta_s)$ and λ_{LwF} are regular term and hyper-parameter for new-old task trade-off tuning.

In our task/difficulty incremental learning setting, we have implemented LwF to retain the old knowledge learnt from previous encountering segment data with different environmental difficulty levels or background distribution variants.

III. EXPERIMENT

To explore the stability and plasticity of task incremental learning for robotic vision and to compare performances across different lifelong learning methods, we have defined multiple difficulty experimental settings and implemented three methods (EWC, SI, and LwF) on different protocols.

A. EXPERIMENTAL SETTINGS

As is shown in Table 1, we have defined three difficulties for each environmental factor. Motivated by the human brain learning process and real-world assistive robotics applications, a data pre-processing had been executed with two steps:

- Segmentation: 3 difficulty degrees have been divided into 9 segments each factor, with the equal number of images per segment since in one level's training data, the poses vary a lot in the taken video. In this case, for each factor, segment 1-3, 4-6, 7-9 belonged to level 1, 2, 3 respectively. We have given a brief explanation of the experiment such as "illumination": the 3-level factor of the dataset is further split into 3 segments for each based on the different views of each object. Thus, we have 9 batches of data (3-level factor, 3 segments for each level) in total and indexed as segment 1-9.
- Shuffling: A shuffle operation has been done in these nine segments. Since in real-world applications, the robots often encounter with dynamic environments with shuffled difficulty levels instead of increasing or decreasing the difficulty levels of the environment all the time.

We have conducted separated experiments on four factors, and the experiment for each factor was carried out in the same way (same backbone model, train/test split, hyper-parameters selection). The experiment setting diagram is provided in Figure 2.

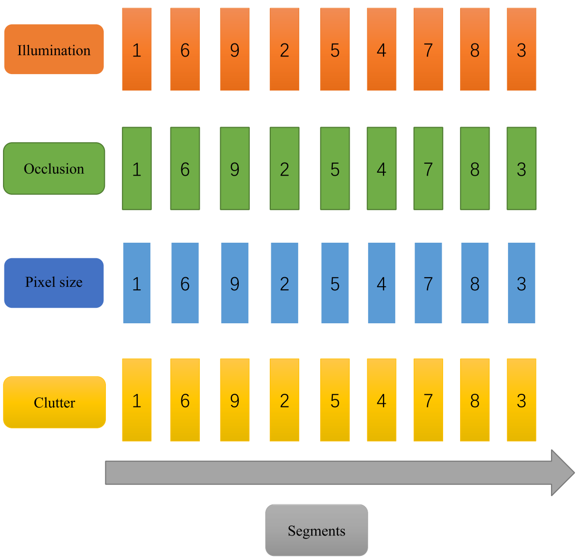

FIGURE 2. Experiment pipeline overview: 4 separated experiments with shuffled segments difficulty incremental data based on 4 factors: illumination, occlusion, pixel size and clutter. For each factor, we have 9 batches/segments of data (3-level factor, 3 segments for each level) and indexed as segment 1-9. For each segment train/test process, we trained on current segment and tested the model on all 9 segments' testing data.

For each training tasks, we have tested on all segment testing data. That means each time we only trained/fine-tuned the one specific segment data and tested on all three levels. In this context, the difficulty of this task is mostly caused by the concept/distribution drift between tasks under different levels' testing data.

In the new dataset [13], the original data has been split into four factors. Here we have picked the part of the released dataset: each factor includes 9 segments, each of them with 3100 training samples, 700 testing samples, and 34 classes. The backbone deep neural network model for feature extraction we used is MobileNetV2 [21]. We set 50 epochs and set batch size (the size of mini-batch during training processes) as 64 for each training task. For each task, we set 50 epochs to fine-tune the model. We take 5-fold cross-validation method to select hyper-parameters of the models for each independent factor's experiment (including learning rate, λ in Equation 1 and Equation 2, etc). We have conducted 5 times cross-validation each segment training. In "illumination" experiment, we chose learning rate $= 0.1$ for all methods, $\lambda_{EWC} = 1.75$ for EWC, $\lambda_{SI} = 2.5$ for SI and $\lambda_{LwF} = 1.5$ for LwF. The deep learning platform we used was PyTorch, and the GPU hardware are 4 pieces of NVIDIA 1080Ti.

For comparison, we also provide two training schemes without any lifelong learning techniques.

- Naive training: We train our model on the first task (such as recognizing objects under the environment with normal illumination, 25**%** **occlusion**, low clutter, and lager than 200×200 pixels of objects) and fine-tuned the model on the second task (recognizing objects under the environment with normal illumination, 50**%** **occlusion**, low clutter, and lager than 200×200 pixels of objects), the same for the next tasks via changing one of the environment factors. This scheme can be seen as transfer learning.
- Cumulative training: We train on the first task, and for the second task, we fine-tune our model using both first and second task's training data. This scheme can be seen as multi-task learning, which utilizes all the encountered data to train the current model. We note that both naive training and three lifelong learning algorithms in this paper do not need to have access to the previously learned data when learning the current task. While cumulative training needs all the task data.

B. EVALUATION METRICS

To compare the performance over time for lifelong learning metrics inspired by previous research, we evaluated the strategies on 4 metrics, including accuracy, backward transfer, forward transfer, and overall accuracy. Matrix $A \in \boldsymbol{A}^{N \times N}$ represents train-test accuracy matrix. There are N tasks in total, and the current task index was n. $A_{i,j}$, an entry of A, denotes the accuracy on task j's test set when trained on task i's training set. The matrix is shown below, meaning each accuracy $A_{i,j}$ in one Lifelong Learning (LL) process with N training and testing sets (denoted as i and j in our setting) respectively. Thus, accuracy is the average value of elements on and below diagonal of $A_{i,j}$, backward transfer and forward transfer equals the average value of elements below, and above the diagonal of $A_{i,j}$ respectively. Overall accuracy is the average value of all elements in $A_{i,j}$ [22].

LL	$Test_1$	$Test_2$	$Test_3$	...	$Test_N$
$Train_1$	$A_{1,1}$	$A_{1,2}$	$A_{1,3}$	...	$A_{1,N}$
$Train_2$	$A_{2,1}$	$A_{2,2}$	$A_{2,3}$	...	$A_{2,N}$
$Train_3$	$A_{3,1}$	$A_{3,2}$	$A_{3,3}$	...	$A_{3,N}$
...	...	...	...	...	...
$Train_N$	$A_{N,1}$	$A_{N,2}$	$A_{N,3}$	...	$A_{N,N}$

1) ACCURACY

Accuracy measures strategies' performances on both current and previous tasks and can be calculated by average test precision on all tasks encountered (Equation 3).

$$\text{Accuracy} = \frac{\sum_{i \geq j}^{N} A_{i,j}}{\frac{N(N+1)}{2}} \tag{3}$$

2) BACKWARD TRANSFER

Backward Transfer (BWT) represents the performance on previous tasks, which could be considered as the representation of overcoming forgetting ability for each lifelong learning method. We evaluate BWT by average test accuracy on each previous task (Equation 4).

$$\text{BWT} = \frac{\sum_{i > j}^{N} A_{i,j}}{\frac{N(N-1)}{2}} \tag{4}$$

3) FORWARD TRANSFER

Forward Transfer (FWT) considers the performance on future tasks, which is common to be seen in real-world assistive robot cases. Our learning model inside the robots cannot be trained on each possibility of dynamic environments. When dealing with a new environment at a new difficulty level, how robot learning models behave mattered. We have evaluated FWT by average test accuracy on each future task (Equation 5).

$$\text{FWT} = \frac{\sum_{i < j}^{N} A_{i,j}}{\frac{N(N-1)}{2}} \tag{5}$$

4) OVERALL ACCURACY

Overall Accuracy considers the performance of the learning system over time and computed by test accuracy on all tasks (Equation 6).

$$\text{Overall} - \text{Accuracy} = \frac{\sum_{i,j}^{N} A_{i,j}}{N^2} \tag{6}$$

IV. RESULTS

We have evaluated four metrics, including accuracy, backward transfer, forward transfer, and overall accuracy, on EWC, SI and LwF strategies together with naive and cumulative training modes in different difficulty levels based on four factors: illumination, occlusion, the angle/distance between the camera and objects and clutter.

The results have been shown in Figure 3.

Four metrics for each factor were provided, and the x/y axis represented the number of encountered tasks and the values of metrics respectively. Each row indicates one separated experiment based on one factor (illumination, occlusion, pixel size, and clutter). For every sub-figure in Figure 3, each metric has been computed several times (8 times for BWT and FWT, 9 times for Accuracy and Overall Accuracy). For example, in the "illumination" experiment, we have computed four metrics (Accuracy, Backward Transfer, Forward Transfer, and Overall Accuracy) each time when we encounter a new task.

For all experiments, we have run ten times and recorded the mean value (see points in each result) and standard deviation (see error bar in each result). Note that for Backward Transfer, no recording on task 1 has been provided since there existed no Backward Transfer results at the moment of task 1, similar reason for no task 9's Forward Transfer provided.

From the results, these three most reported regularization strategies have failed with the increase in encountered batches across all four metrics with indistinguishable performance comparing to the naive training mode. More specifically, several phenomena can be found, and both intuitive and theoretical explanations can support those phenomena.

- In our experiment, we have trained certain condition such as "Normal" and tested over all previous tasks at each time. For each task, we only trained/fine-tuned dataset sampled from one specific level and tested on all three levels per factor. In this context, the difficulty is mostly caused by the concept/distribution shift between tasks under different levels' testing data. The testing is progressively more diverse.
  All methods held high accuracy in task 1 (can be seen in the first column of Figure 3) but then decreased sharply in task 2. This is because, for task 1, both training and testing data has been all sampled from the same distribution so the learning system can obtain relatively good performance, but for testing after task 2's training, they forget some information learned in task 1's learning process. Thus, the accuracy drops a lot. For each task, these methods only performed well on its current task's testing set while failed on other level tasks. The current task's accuracy has been pretty high (almost 88%-95%), and other tasks tended to be low (15%-30%). While our experimental metrics focused on both current tasks and other tasks, so the accuracy appeared to be similar.
- In some cases, (for example, Task 7's Backward Transfer, and Task 4's Accuracy in the experiment based on illumination), naive training scheme may not show the worst performance. These three regularization methods sometimes cannot address the concept/distribution drift problem. The main reasons these methods fail to retain old information and obtain new knowledge are that 1) In this difficulty incremental learning scenario, heir regularized term cannot represent the valuable parameters' information from previous tasks. 2) The concept/ distribution drift problem in OpenLORIS-Object dataset

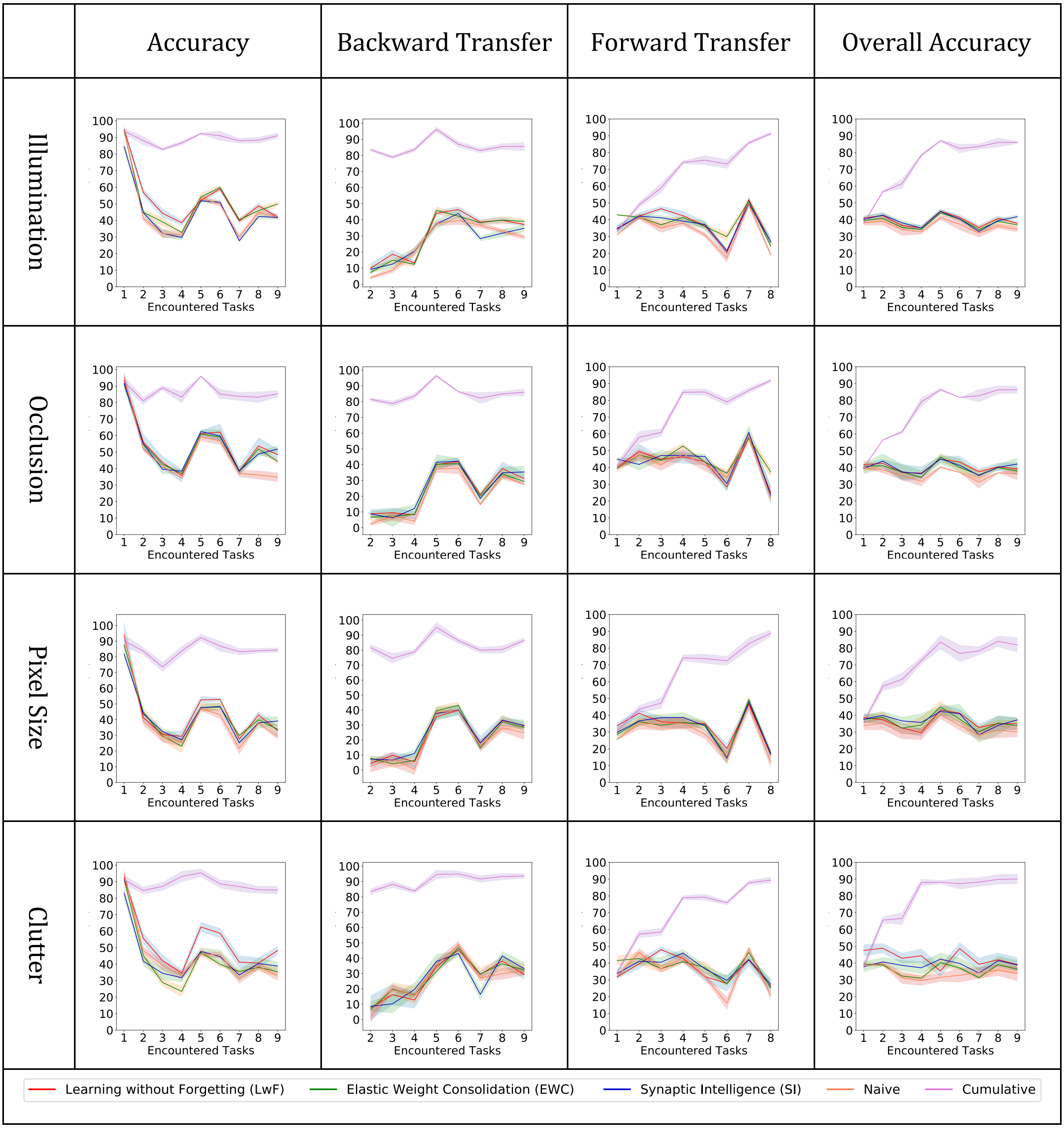

FIGURE 3. **Each row indicates one separated experiment based on one factor (illumination, clutter, pixel size or occlusion). Four metrics (columns) are used for evaluating the 5 methods. For each sub-figure, it correspond to one metric for one factor, and the curves indicate 5 methods, respectively. The x-axis is the number of encountered tasks, and the y-axis is the metric (all of four metrics have maximum value "100%") evaluated after learning current task. Best view in color.**

is more substantial than other benchmark datasets, while the distribution gap between previous and current tasks is large. When the algorithms optimize the loss function with the regularized term, the learnt information may cause interference on current tasks' learning. This may cause their precision on the current task even lower than naive training scheme.

- In most results, the naive training scheme and cumulative training scheme can be seen as the lower bound and upper bound respectively.

- For all conditions, the curve showed a similar trend since the data distribution changed a lot during sequential task learning, so the visual systems developed cannot perform well for all the tasks consistently. Furthermore, for the instance or class incremental learning process reported in previous work [10], [12], [23], they are easier to improve the recognition capability under the lifelong or continual learning scheme. However, the task difficulty change (task incremental) should be more challenging with relatively sharper domain/concept drifts, which pose novel problems for exiting lifelong learning algorithms.
- The three regularization based learning algorithms fail because (1) they only deal with smoother concept drift such as permutation MNIST dataset compared with OpenLORIS-Object dataset; (2) these three methods are far from being applied to object recognition tasks under ever-changing difficulty, the potential improvement for them is to design the algorithms that more tightly coupled with the classifiers (current they are loosely coupled, meaning the lifelong learning algorithms are independent with the object recognition techniques). From these experiments, we have found having achieved high performances over naive benchmarks (such as the three learning methods did) sometimes avoid further development of real applicable methods, because the researchers focus on too much about the naive benchmark themselves without considering the real challenges. We do believe the challenges themselves should be specifically modeled (e.g. with latent variable models for intrinsic unknown challenges) in order to thoroughly address the problems.

V. CONCLUSION

This work introduces lifelong/continual object recognition methods for long-term robot deployment based on a novel robotic vision dataset. The dataset captures commonly observed variations in illumination, occlusion, the angle/distance between cameras and objects, and clutter of recordings in real-world. Using the new dataset and benchmarks, we find the most widely-used methods (EWC, SI, and LwF) are quite limited with performance similar to naive training mode across all metrics. Our results have shown that the development of novel algorithm to tackle these practical factors is urgent and necessary. The dataset made available will serve the testbed for the real-world deployment of future methods for mobile assistive robots.

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