Fast Object Segmentation Learning with Kernel-based Methods for Robotics

Federico Ceola[1,2], Elisa Maiettini[1], Giulia Pasquale[1], Lorenzo Rosasco[2,3] and Lorenzo Natale[1]

Abstract— **Object segmentation is a key component in the visual system of a robot that performs tasks like grasping and object manipulation, especially in presence of occlusions. Like many other computer vision tasks, the adoption of deep architectures has made available algorithms that perform this task with remarkable performance. However, adoption of such algorithms in robotics is hampered by the fact that training requires large amount of computing time and it cannot be performed on-line.**

In this work, we propose a novel architecture for object segmentation, that overcomes this problem and provides comparable performance in a fraction of the time required by the state-of-the-art methods. Our approach is based on a pre-trained Mask R-CNN, in which various layers have been replaced with a set of classifiers and regressors that are re-trained for a new task. We employ an efficient Kernel-based method that allows for fast training on large scale problems. Our approach is validated on the YCB-Video dataset which is widely adopted in the computer vision and robotics community, demonstrating that we can achieve and even surpass performance of the state-of-the-art, with a significant reduction ($\sim$6$\times$) of the training time.

The code to reproduce the experiments is publicly available on GitHub[1].

I. INTRODUCTION

Object segmentation is a key task in computer vision and robotics. A precise localization of the object on the image plane is key to solve problems like pose estimation [1], [2], [3], refinement [4], [5] and grasping or manipulation [6]. Like many other computer vision tasks (e.g., image classification and object detection), for decades this was mostly addressed with feature extraction (e.g., sparse coding [7], Fisher vectors [8]) followed by Kernel methods [9] or structured prediction approaches [10], [11]. In recent years, instead, end-to-end training of deep architectures became mainstream since it showed to provide superior performance [12], [13], [14].

However, deep learning is known to require large training data to optimize complex architectures with expensive and long training procedures. While the problem of training data

has recently been alleviated by synthetic image generation [15], [16], the computational burden remains.

Lately, the literature of one-shot and few-shot object segmentation in video [17] presented methods based on the idea of fine-tuning only part of the network on-line [18], [19]. This approach can learn to segment novel objects in shorter time than standard end-to-end approaches, while keeping performance. However, the procedure of fine-tuning a deep network in general does not guarantee generalization properties, since it involves a non convex optimization and several hyper-parameters, while it can be still prohibitive for robotic settings which require learning to happen very fast (e.g., in seconds or minutes).

Recently, it was shown that pre-trained deep features can be efficiently re-used also to train Kernel-based methods for tasks like image classification [20] object detection and even segmentation [21], [22]. The advantage of Kernel-based methods, among others, is that the number of hyper-parameters to tune is smaller (e.g. in [23], one regularization parameter, one Kernel parameter) and convergence and generalization properties are guaranteed [23]. This approach was recently adopted to achieve high performance and remarkably faster training times in interactive object learning applications for object recognition [24] and detection [25] in robotics. By relying on the above pipelines, a robot can observe a short image sequence of the objects of interest and seamlessly train to detect them right afterwards[2,3].

In this paper, we build on this prior work and present a method to re-use general-purpose deep features (e.g., pre-trained on COCO [26]) to train Kernel methods for the *dense* task of image segmentation. As evidenced from prior work [25], [22], [21], the main challenge lies in the difficulty of training a *non-linear* classifier over the *large* training sets that characterize object detection and segmentation problems (where each sample is a region or a single pixel in an image).

To this end, we feed deep features to FALKON [23], a recently proposed Nyström-based Kernel method optimized for large-scale problems. We instantiate one per-pixel FALKON classifier for every class and train it on pixel-wise features extracted from the second-last layer of the network. We first solve the detection task by applying the same approach, which was presented in [25]. Then, we feed the dense features extracted from the detected regions to

[1]Federico Ceola, Elisa Maiettini, Giulia Pasquale and Lorenzo Natale are with Humanoid Sensing and Perception, Istituto Italiano di Tecnologia, Genoa, Italy `name.surname@iit.it`

[2]Lorenzo Rosasco and Federico Ceola are with Laboratory for Computational and Statistical Learning and with Dipartimento di Informatica, Bioingegneria, Robotica e Ingegneria dei Sistemi, University of Genoa, Genoa, Italy

[3]Lorenzo Rosasco is also with Istituto Italiano di Tecnologia and Massachusetts Institute of Technology, Cambridge, MA `lrosasco@mit.edu`

[1]`https://github.com/robotology/online-detection`

[2]`https://youtu.be/HdmDYIL48H4`
[3]`https://youtu.be/eT-2v6-xoSs`

FALKON classifiers to perform figure-ground segmentation within each region. To tackle the well-known problem of dataset (positive-negative) imbalance which characterizes the task of object detection, we use the bootstrapping technique from [25]. Instead, to manage the great quantity of data in the figure-ground segmentation task, we apply data subsampling in our training procedure.

As network, we use the region-based Mask R-CNN [13], to which we basically replace every output layer with a set of FALKON classifiers or regressors. The resulting architecture is clean and flexible, allowing to easily train accurate instance segmentation on small datasets in a few minutes, but possibly also on large ones.

We benchmark our method on the YCB-Video dataset [1], a state-of-the-art benchmark for pose estimation and tracking in challenging conditions for robotics, featuring clutter and occlusion across varied objects. In fact, while pose estimation results are widespread over this latter, but also other robotics datasets (see, e.g., the BOP challenge [27]), it is less common for robotic papers to present the partial results over the segmentation task –which, however, is almost always part of their pipelines. Hence, we also hope that this work could pave the way to other works in robotics, to present not only pose estimation but also intermediate segmentation results.

The remaining of this paper is organized as follows. In Sec. II we review the state-of-the-art in the fields of instance segmentation and efficient learning strategies for visual tasks in robotics. Then in Sec. III, we describe the proposed approach and in Sec. IV we report on the performed empirical validation. Finally, in Sec. V, we summarize the main contributions and identify directions for future works.

II. RELATED WORK

In this section, we overview the main state-of-the-art approaches for object segmentation (Sec. II-A), then we present the literature that tackles the problem of fast adaptation of robotic vision systems to novel tasks (Sec. II-B).

A. Object instance segmentation

The task of *instance segmentation* [14] aims at classifying all the pixels in an image, while identifying different instances of the categories of interest. Note that, this task is different from *semantic segmentation*, which has the similar objective of classifying every pixel of an image but not being aware of the different instances. While the field of semantic segmentation is mainly dominated by approaches based on Fully Convolutional Networks (FCNs) [12], [28], the literature in instance segmentation can be divided in the following three groups.

Region-based approaches. Methods in this group split the segmentation task into four main stages: (i) a convolutional feature map is generated by a FCN applied to the whole image, (ii) a list of Regions of Interest (RoIs) is generated by a region proposal method, (iii) a RoI pooling layer [29] warps each RoI and extracts per-RoI features from the convolutional map and, finally, (iv) two sibling shallow Neural Networks predict detections and masks for each feature map. The main representative example of this group is Mask R-CNN [13] which extends the object detection architecture Faster R-CNN [29] by adding, in parallel to the final detection layers, a further output layer for binary mask prediction. Note that, this is in contrast to latest approaches [30], [31], [32], where the classification depends on the prediction of the masks. Mask R-CNN is devised as a monolithic architecture which trains end-to-end, via stochastic gradient descent and back-propagation, all the components for region proposals and feature extraction, object detection and segmentation. The network optimization is carried out by minimizing a "multi-task loss" [29], [13], which accounts for the contribution of classification, bounding box and mask precision (see [29], [13] for details).

Pixel-based approaches. Methods of this group predict a so-called "auxiliary" information for each pixel (like, e.g, energy levels [33]) and then a clustering algorithm groups pixels into object instances based on such information. An example of this approach is presented in [33], where the watershed transform is combined with a deep convolutional network to produce an energy map of the image where object instances are represented as energy basins. Then, they perform a cut at a single energy level to yield connected components corresponding to object instances.

Snake approaches. Methods of this group deform an initial coarse contour to the object boundary by optimizing a handcrafted or learned energy measure with respect to the contour coordinates. In [34], for instance, the presented pipeline uses a graph convolutional network to predict vertex-wise offsets for contour deformation. In [35], instead, the object's contour is not treated as a general graph, but it leverages the cycle graph topology and uses the circular convolution for efficient feature learning on a contour.

All the aforementioned methods of the state-of-art are "monolithic" deep architectures, trained end-to-end via back-propagation and stochastic gradient descent, with long training times that are not suited for on-line robotic applications. In this work, we propose a region-based method for object segmentation that, building on previous work [25], addresses this issue, allowing for fast model learning.

B. Fast object detection methods in robotics

Fast and efficient adaptation to novel tasks is critical for robots that need to operate in unconstrained environments. Previous works in robotics analyze this problem and propose solutions for object recognition [24] and object detection [36], [25]. In both cases, the proposed pipelines rely on hybrid architectures that integrate deep Convolutional Neural Network's (CNN) feature descriptors with efficient "shallow" Kernel-based methods (like, e.g., FALKON [23]) for respectively classification or detection. In these works, the key aspect to achieve on-line training time is to decouple the learning of the features and region proposals extractor from the optimization of the Kernel-based methods.
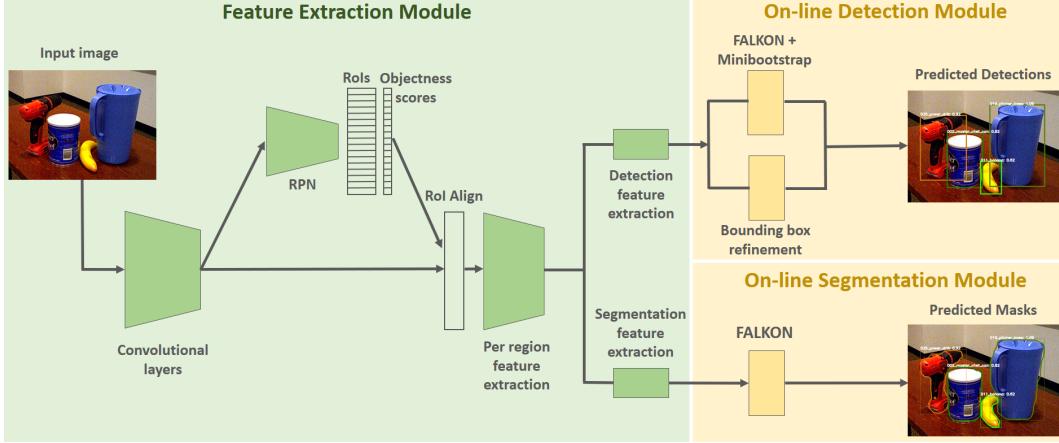
Fig. 1: Overview of the proposed pipeline. The *Feature Extraction Module* is composed of Mask R-CNN's first layers trained off-line on the FEATURE-TASK. For each input image, it extracts per RoI features to train on-line on the TARGET-TASK the *On-line Detection Module* and the *On-line Segmentation Module*. The *On-line Detection Module* classifies the RoIs and predicts the corresponding detections. The *On-line Segmentation Module* predicts masks for each detection. Note that the picture represents the pipeline at training time. At test time, the detection output is fed as input to the RoI Align.

Moreover, in [25] an approximated bootstrapping procedure for selecting hard negative samples has been proposed, to address the well-known foreground-background imbalance problem in object detection.

In this work, we extend the pipeline proposed in [25], to also perform object segmentation. Following the same principle as in [25], in our proposed approach, the training of the features and region proposals extractor is decoupled by the optimization of the detection and segmentation methods, allowing for a fast model re-adaptation.

III. METHODS

In this work, we present an instance segmentation method, which allows to learn to predict masks of previously unseen objects (referred to as TARGET-TASK) in a fraction of the time required by state-of-the-art approaches. To do this, it relies on some components of a deep learning based instance segmentation network trained once and off-line on the available data, depicting a different set of objects (referred to as FEATURE-TASK).

In this section, we describe the proposed approach. Sec. III-A provides an overview of the pipeline, while in Sec. III-B the proposed on-line learning strategy for instance segmentation is described.

A. Overview of the pipeline

The pipeline proposed in this work is mainly composed of three modules, as depicted in Fig. 1:

- The **Feature Extraction Module** employs the first layers of the Mask R-CNN architecture, trained on the FEATURE-TASK, to extract two sets of convolutional features for a set of RoIs, one for **On-line Detection** and one for **On-line Segmentation**.
- The **On-line Detection Module** uses the per-region features computed by the feature extractor to predict

their class and to refine their bounding box with the approach described in [25].

- The **On-line Segmentation Module**, instead, predicts the masks of the instances contained in the RoIs with the approach proposed in this work and described in Sec. III-B. As the previous module, also this module is trained on the TARGET-TASK.

The main contribution relies on the latter module. Indeed, we propose a fast and efficient learning strategy that allows to update the instance segmentation model in few minutes. Moreover, we integrate it in the on-line detection pipeline presented in [25], extending it and proposing a novel approach. This permits fast adaptation time as new data is available for both object detection and segmentation.

Learning protocol. Our learning procedure is composed of two stages. Firstly, Mask R-CNN is trained off-line on the FEATURE-TASK via backpropagation, following the training protocol proposed in [13]. Then, the on-line training of both the detector and the mask predictor on the TARGET-TASK are performed in three sub-steps. First, some of the layers of the Mask R-CNN architecture learned in the first phase on the FEATURE-TASK (specifically the backbone, the RPN and the convolutional layers following the Roi Align, depicted as green blocks in Fig. 1), are used to jointly extract the two sets of features needed to train the *On-line Detection Module* and the *On-line Segmentation Module* (represented by yellow blocks in Fig. 1). These two modules are then sequentially trained with the on-line learning strategy described in Sec. III-B.

B. On-line learning strategy

As mentioned in Sec. III-A, the trainings of the *On-line Detection Module* and of the *On-line Segmentation Module* are performed by employing two different sets of features computed by the *Feature Extraction Module*. These

are extracted in two different points of the Mask R-CNN architecture. Specifically, features necessary to train the *On-line Detection Module* are extracted from the set of one-dimensional tensors, which in Mask R-CNN are given as input to the last fully connected layers of the detection head. Features necessary to train the *On-line Segmentation Module*, instead, are contained in the convolutional feature maps produced as output by the penultimate convolutional layer of the mask head in Mask R-CNN. Once the sets of features are extracted for all the training images, the *On-line Detection Module* and the *On-line Segmentation Module* can be trained with the procedures described below.

On-line Detection. For the training of the *On-line Detection Module*, we adopt the method described in [25], but we use the improved implementation of the *Feature Extraction Module* proposed in [37]. Indeed, such improvement allows to increase the quality of the features, due to the substitution of the first layers of Faster R-CNN [29], with the ones from Mask R-CNN [13]. As in [25], the last fully connected layers of the detection head in Mask R-CNN are substituted with N FALKON [23], [38] binary classifiers (N being the number of classes of the TARGET-TASK) for class prediction, and by $N \times 4$ Regularized Least Squares (RLS) regressors for the refinement [22] of the RoIs proposed by the RPN. To deal with the well-known problem of foreground-background imbalance and with the high redundancy among the negative examples in object detection problems [39], the N FALKON classifiers are trained with the *Minibootstrap* proposed in [25]. This procedure is an adaptation of the Hard Negatives Mining strategy [22] and it allows to train the classifiers in a few seconds by visiting a random subset of negative examples.

On-line Segmentation. In Mask R-CNN [13], the mask head is a shallow Fully Convolutional Network (FCN), which for every RoI computes N squared masks (one for each of the N classes) of fixed size $s \times s$. In particular, the last layer of the segmentation branch (i.e., the per-pixel mask predictor) is a convolutional layer with N channels, kernel size 1 and stride 1 that receives as input a convolutional feature map of size $s \times s \times f$ (where f is the number of channels). Therefore, the output tensor of the segmentation head has dimension $s \times s \times N$ and the ijn^{th} element of such tensor represents the probability of the pixel in the location ij of belonging to an instance of the nth class. In this work, we substitute the N kernels for per-pixel classification with N FALKON binary classifiers. We flatten the $s \times s \times f$ feature map into a list of $s \times s$ feature tensors of size f associated to specific locations in the RoIs and use them as samples to train the FALKON classifiers. At training time, we consider the ground-truth bounding boxes as RoIs. The ij^{th} element of the input feature map of size $s \times s \times f$ is considered as a positive training sample for the nth classifier if the ij^{th} pixel of the associated ground-truth mask belongs to the foreground and the ground-truth class is n. Otherwise, if it is a background pixel within a ground-truth bounding box of class n, it is considered as a negative sample for the nth classifier. To speed-up the training procedure, both the positive and the negative instances are subsampled by a fixed factor r. We employ FALKON to address the per-pixel classification problem since, as shown in [25] (specifically, refer to Tab. 6 in [25]), among other equivalent choices, it allows to achieve the best time-accuracy trade-off (refer to [23] for details).

Hyper-parameters. For both the detection and segmentation modules, we use FALKON with a Gaussian Kernel. The main hyper-parameters of the proposed method are:

- The standard deviation σ of the Gaussian Kernel, the regularization parameter λ and the number of Nyström centers M of the FALKON classifiers of both the *On-line Detection Module* and the *On-line Segmentation Module*.
- The *Minibootstrap* parameters to train the *On-line Detection Module*, i.e., the number of batches n_B and the size of such batches BS.
- The sampling factor r of the training examples in the *On-line Segmentation Module*.

For our experiments, we rely on the criterion proposed in [25] to set the *Minibootstrap*'s parameters, we cross-validate the FALKON's parameters as explained in Sec IV-A and we report on an empirical analysis of the impact of the sampling factor r.

IV. EXPERIMENTS

In this section, we report the experiments performed to validate the proposed approach. In Sec. IV-A, we describe the experimental setup. In Sec. IV-B, we provide the results obtained on the YCB-Video benchmark. Finally, in Sec. IV-C, we report on ablation studies to analyze our approach.

A. Experimental setup

In this work, we consider Mask R-CNN as baseline for comparison with the proposed pipeline (**Ours**). We start with Mask R-CNN trained on the FEATURE-TASK and we fine-tune the output layers on the TARGET-TASK (i.e., the fully connected layers for detection and the last convolutional layer for masks prediction). We refer to this architecture and training method as **Mask R-CNN (output layers)**. We use ResNet50 [40] as backbone of Mask R-CNN for both the **Mask R-CNN (output layers)** baseline and the *Feature Extraction Module* of the proposed approach (**Ours**). To set the training hyper-parameters, for both methods we perform a cross-validation on a validation set. Specifically, the model chosen for the **Mask R-CNN (output layers)** baseline has been trained for the minimum number of epochs at which the highest segmentation accuracy is achieved on the validation set. In **Ours**, instead, the validation set is used to select σs and λs of the FALKON classifiers, both in the *On-line Detection Module* and in the *On-line Segmentation Module*. To compare the performance between the two approaches, we consider three metrics: the mean Average Precision (mAP), as defined in [41] of the predicted detections (**mAP bbox(%)**) and of the predicted

Method	mAP50 bbox(%)	mAP50 segm(%)	mAP70 bbox(%)	mAP70 segm(%)	Train Time
Mask R-CNN [13] (output layers)	**76.87**	74.12	68.56	64.80	1h 57m 1s
Ours	76.46	**74.66**	**68.71**	**64.96**	**19m 32s**

TABLE I: Benchmark on the YCB-VIDEO dataset. We compare the accuracy achieved by (**Mask R-CNN (output layers)**) (first row) and by the proposed approach (**Ours**) (second row).

Fig. 2: Randomly chosen predictions of **Ours** on the YCB-Video $keyframe$ set.

masks (**mAP segm(%)**) and the training time. Concerning the bounding boxes and masks IoU to be considered as positives matches in the mAP computations, we set the thresholds to 50% and 70%. As regards the training time[4], for **Mask R-CNN (output layers)** it is the time necessary to fine-tune Mask R-CNN via backpropagation. For **Ours**, instead, it is composed of the feature extraction time and of the training time of the on-line modules. The former one in practical robotic applications can happen during the data acquisition phase[2,3], which can be performed, for instance, as in [42], [43], [44], [45], where the ground-truth is collected with automatic procedure.

Datasets. In our experiments we consider the YCB-Video [1] dataset. Specifically, we use as training set a sample of the 80 training sequences, by selecting one every ten frames, resulting into a set of 11320 images. For testing, instead, we use the 2949 images included in the *keyframe* set. To select the training hyper-parameters, according to the training protocol described in Sec.IV-A, we use a set of 1000 images, randomly sampled from the 12 test sequences, which are not included in the *keyframe* set. The 80 categories in the MS COCO [26] dataset, instead, compose the FEATURE-TASK in some of our experiments.

B. Benchmark on the YCB-Video dataset

We validate the proposed on-line segmentation approach by considering the 21 objects from the YCB-Video dataset as TARGET-TASK and MS COCO as FEATURE-TASK. As described in Sec. IV-A, we compare the performance obtained by our approach (**Ours**), with the **Mask R-CNN (output layers)** baseline. As in [25], to train the *On-line Detection Module* we set the *Minibootstrap*'s batch size BS

to 2000, but, given the higher amount of training images with respect to the benchmark reported in [25] (Table 2), we increase the number of batches n_B to 15. The number of Nyström centers M of the FALKON classifiers of both the *On-line Detection Module* and the *On-line Segmentation Module* is set to 2000. The sampling factor r of the segmentation training samples is set to 0.3 (refer to Sec. IV-C for an analysis of the impact of this parameter).

Results reported in Tab. I show that our approach, while being $\sim$6 times faster than the baseline, outperforms **Mask R-CNN (output layers)** in the segmentation accuracy computed with both IoU thresholds, while achieving comparable performance in terms of detection mAP. Train time of **Ours** is composed of 18min:23s for feature extraction, 35s to train the *On-line Detection Module* and 34s to train the *On-line Segmentation Module*. This shows that, once the features are extracted, the TARGET-TASK can be learned extremely fast. We report in Fig. 2, some random images from the test set with the overlaid predicted masks.

C. Ablation studies

In this section, we provide three ablation studies of the proposed pipeline to further validate our approach. Firstly, we evaluate segmentation accuracy by decoupling such task from the detection one. Then, we analyze the impact on accuracy and training time of the sampling factor r (see Sec. III-B). Finally, to compare the accuracy of our method with the one of Mask R-CNN fully trained on the TARGET-TASK, we benchmark our approach in a scenario in which FEATURE-TASK and TARGET-TASK correspond.

Segmentation of ground-truth bounding boxes. In Mask R-CNN [13] and in our pipeline, the segmentation performance depends on the detection. To separately evaluate the segmentation errors, we consider the ideal case in which the bounding boxes proposed by the detection branch correspond to the ground-truths. FEATURE-TASK
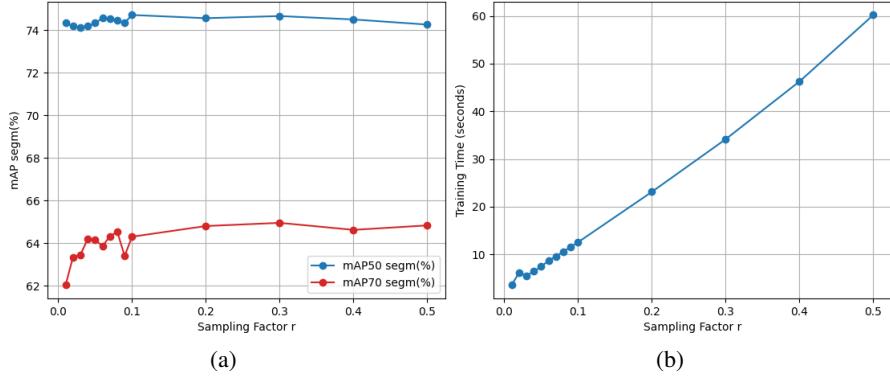
Fig. 3: Segmentation mAPs and training time for increasing values of the sampling factor r.

Method	mAP50 bbox(%)	mAP50 segm(%)	mAP70 bbox(%)	mAP70 segm(%)
Mask R-CNN [13] (full)	89.76	91.29	86.05	**80.41**
Ours	**90.98**	**92.28**	**86.90**	80.17

TABLE II: Ablation study with YCB-VIDEO dataset used as both FEATURE-TASK and TARGET-TASK. We compare the results of the full training of Mask R-CNN (**Mask R-CNN (full)**) (first row) with the proposed approach (**Ours**) (second row) considering as feature extractor the weights learned with the training in the first row.

and TARGET-TASK are the same as the ones considered in Sec. IV-B. The achieved segmentation mAP is **94.66** and **81.78** when the IoU thresholds are set respectively to 50% and 70%. We compare the obtained results with **Mask R-CNN (last layers)** as in Sec. IV-B where, as for **Ours**, we consider the ground-truth boxes as proposed detections. For the baseline, the segmentation mAP is **93.70** and **79.46** when the IoU thresholds are set to 50% and 70%, showing the effectiveness of the proposed *On-line Segmentation Module*.

Training samples vs. training time and mAP. Since the time required to train the *On-line Segmentation Module* is critical in robotic applications, we provide an analysis of how the choice of the sampling factor r affects both the training time and the segmentation accuracy of such module. As it can be observed in Fig. 3a, the sampling factor r can be pushed to the extreme while preserving the segmentation accuracy in terms of both the considered IoU thresholds. By using a small fraction of training examples, the training times can be reduced until they become in the order of a few seconds, as it can be noticed in Fig. 3b. When the sampling factor r is 0.01, the number of per class positives and negatives training samples is ranging from $\sim 1k$ to $\sim 4k$.

YCB-Video for both FEATURE-TASK and TARGET-TASK. The goal of this work is to quickly learn to segment previously unseen objects. To this aim, in Sec. IV-B we showed the efficiency of the proposed approach when the TARGET-TASK is different form the FEATURE-TASK. Nevertheless, to further validate our pipeline, we evaluate the performance of our method when the two tasks correspond. In particular, we set them by considering the 21 object identification task in the YCB-Video dataset (the TARGET-TASK defined in Sec. IV-A). In this case, we train, as baseline, the entire Mask R-CNN network (starting from the weights pre-trained on the COCO dataset) on

the TARGET-TASK (**Mask R-CNN (full)**). Then, we use such weights to extract the features needed to train the *On-line Detection Module* and the *On-line Segmentation Module* with the approach described in Sec. III-B (**Ours**). The obtained accuracy are reported in Tab. II. Since the full training of Mask R-CNN on the TARGET-TASK is necessary both to obtain a baseline for our comparison and subsequently to train our pipeline, for this experiment the training times cannot be compared. Results reported in Tab. II show that, as in previous experiments, our approach provides comparable performance with respect to the baseline in terms of detection and segmentation mAP with both the IoU thresholds.

V. CONCLUSIONS

Fast learning and efficient adaptation are fundamental for robots that need to quickly adjust their vision systems to ever-changing environments. In this perspective, this work presents a system for instance segmentation that extends and improves previous on-line learning approaches for object detection [25]. The proposed method combines Mask R-CNN for feature extraction and two sets of FALKON classifiers to efficiently perform object detection and segmentation. The resulting pipeline allows for fast adaptation to novel tasks in a fraction of the time of the deep learning based counter parts, representing a step toward the implementation of more adaptive robotic vision systems.

In Sec. IV-C, we showed that we can achieve high per-pixel prediction accuracy with few training samples. We believe that this can be pushed to the extreme by integrating few-shots learning techniques in the proposed pipeline. Moreover, given the importance of instance segmentation for other more complex tasks, such as 6D pose estimation and object grasping, the proposed approach may represent a starting point towards the on-line adaptation of such tasks.

REFERENCES

[1] Yu Xiang, Tanner Schmidt, Venkatraman Narayanan, and Dieter Fox. Posecnn: A convolutional neural network for 6d object pose estimation in cluttered scenes. 2018.

[2] Sergey Zakharov, Ivan Shugurov, and Slobodan Ilic. Dpod: 6d pose object detector and refiner. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2019.

[3] Chen Wang, Danfei Xu, Yuke Zhu, Roberto Martin-Martin, Cewu Lu, Li Fei-Fei, and Silvio Savarese. Densefusion: 6d object pose estimation by iterative dense fusion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

[4] Yi Li, Gu Wang, Xiangyang Ji, Yu Xiang, and Dieter Fox. Deepim: Deep iterative matching for 6d pose estimation. In *Proceedings of the European Conference on Computer Vision (ECCV)*, September 2018.

[5] Fabian Manhardt, Wadim Kehl, Nassir Navab, and Federico Tombari. Deep model-based 6d pose refinement in rgb. In *Proceedings of the European Conference on Computer Vision (ECCV)*, September 2018.

[6] X. Deng, Y. Xiang, A. Mousavian, C. Eppner, T. Bretl, and D. Fox. Self-supervised 6d object pose estimation for robot manipulation. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3665–3671, 2020.

[7] Jianchao Yang, Kai Yu, Yihong Gong, and T. Huang. Linear spatial pyramid matching using sparse coding for image classification. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1794–1801, 2009.

[8] Florent Perronnin, Jorge Sánchez, and Thomas Mensink. Improving the fisher kernel for large-scale image classification. In Kostas Daniilidis, Petros Maragos, and Nikos Paragios, editors, *Computer Vision – ECCV 2010*, pages 143–156, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg.

[9] B. Fulkerson, A. Vedaldi, and S. Soatto. Class segmentation and object localization with superpixel neighborhoods. In *2009 IEEE 12th International Conference on Computer Vision*, pages 670–677, 2009.

[10] Philipp Krähenbühl and Vladlen Koltun. Efficient inference in fully connected crfs with gaussian edge potentials. In *Advances in neural information processing systems*, pages 109–117, 2011.

[11] Aurélien Lucchi, Yunpeng Li, Kevin Smith, and Pascal Fua. Structured image segmentation using kernelized features. In Andrew Fitzgibbon, Svetlana Lazebnik, Pietro Perona, Yoichi Sato, and Cordelia Schmid, editors, *Computer Vision – ECCV 2012*, pages 400–413, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg.

[12] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015.

[13] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross B. Girshick. Mask r-cnn. *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2980–2988, 2017.

[14] Shervin Minaee, Yuri Boykov, Fatih Porikli, Antonio Plaza, Nasser Kehtarnavaz, and Demetri Terzopoulos. Image segmentation using deep learning: A survey. *arXiv preprint arXiv:2001.05566*, 2020.

[15] Tal Remez, Jonathan Huang, and Matthew Brown. Learning to segment via cut-and-paste. In *Proceedings of the European Conference on Computer Vision (ECCV)*, September 2018.

[16] Maximilian Denninger, Martin Sundermeyer, Dominik Winkelbauer, Dmitry Olefir, Tomas Hodan, Mohamad Elbadrawy Youssef Zidan and, Markus Knauer, Harinandan Katam, and Lodhi Ahsan. Blenderproc: Reducing the reality gap with photorealistic rendering. In *RSS 2020*, 2020.

[17] Sergi Caelles, Jordi Pont-Tuset, Federico Perazzi, Alberto Montes, Kevis-Kokitsi Maninis, and Luc Van Gool. The 2019 davis challenge on vos: Unsupervised multi-object segmentation. *arXiv:1905.00737*, 2019.

[18] P. Voigtlaender and B. Leibe. Online adaptation of convolutional neural networks for the 2017 davis challenge on video object segmentation. *The 2017 DAVIS Challenge on Video Object Segmentation - CVPR Workshops*, 2017.

[19] A. Newswanger and C. Xu. One-shot video object segmentation with iterative online fine-tuning. *The 2017 DAVIS Challenge on Video Object Segmentation - CVPR Workshops*, 2017.

[20] K. Chatfield, K. Simonyan, A. Vedaldi, and A. Zisserman. Return of the devil in the details: Delving deep into convolutional nets. In *British Machine Vision Conference*, 2014.

[21] C. Farabet, C. Couprie, L. Najman, and Y. LeCun. Learning hierarchical features for scene labeling. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8):1915–1929, 2013.

[22] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.

[23] Alessandro Rudi, Luigi Carratino, and Lorenzo Rosasco. Falkon: An optimal large scale kernel method. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 3888–3898. Curran Associates, Inc., 2017.

[24] Giulia Pasquale, Carlo Ciliberto, Francesca Odone, Lorenzo Rosasco, and Lorenzo Natale. Are we done with object recognition? the icub robot's perspective. *Robotics and Autonomous Systems*, 112:260 – 281, 2019.

[25] Elisa Maiettini, Giulia Pasquale, Lorenzo Rosasco, and Lorenzo Natale. On-line object detection: a robotics challenge. *Autonomous Robots*, Nov 2019.

[26] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. Microsoft coco: Common objects in context. In *European Conference on Computer Vision (ECCV)*, Zürich, 2014. Oral.

[27] Tomáš Hodaň, Martin Sundermeyer, Bertram Drost, Yann Labbé, Eric Brachmann, Frank Michel, Carsten Rother, and Jiří Matas. BOP challenge 2020 on 6D object localization. *European Conference on Computer Vision Workshops (ECCVW)*, 2020.

[28] E. Shelhamer, J. Long, and T. Darrell. Fully convolutional networks for semantic segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(4):640–651, April 2017.

[29] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In *Neural Information Processing Systems (NIPS)*, 2015.

[30] Jifeng Dai, Kaiming He, and Jian Sun. Instance-aware semantic segmentation via multi-task network cascades. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3150–3158, 2016.

[31] Yi Li, Haozhi Qi, Jifeng Dai, Xiangyang Ji, and Yichen Wei. Fully convolutional instance-aware semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2359–2367, 2017.

[32] Pedro O Pinheiro, Ronan Collobert, and Piotr Dollar. Learning to segment object candidates. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems 28*, pages 1990–1998. Curran Associates, Inc., 2015.

[33] Min Bai and Raquel Urtasun. Deep watershed transform for instance segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5221–5229, 2017.

[34] Huan Ling, Jun Gao, Amlan Kar, Wenzheng Chen, and Sanja Fidler. Fast interactive object annotation with curve-gcn. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5257–5266, 2019.

[35] Sida Peng, Wen Jiang, Huaijin Pi, Xiuli Li, Hujun Bao, and Xiaowei Zhou. Deep snake for real-time instance segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8533–8542, 2020.

[36] E. Maiettini, G. Pasquale, L. Rosasco, and L. Natale. Speeding-up object detection training for robotics with falkon. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct 2018.

[37] Federico Ceola, Elisa Maiettini, Giulia Pasquale, Lorenzo Rosasco, and Lorenzo Natale. Fast region proposal learning for object detection for robotics. *arXiv preprint arXiv:2011.12790*, 2020.

[38] Giacomo Meanti, Luigi Carratino, Lorenzo Rosasco, and Alessandro Rudi. Kernel methods through the roof: handling billions of points efficiently. *arXiv preprint arXiv:2006.10350v1*, 2020.

[39] Tsung-Yi Lin, Priya Goyal, Ross B. Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2999–3007, 2017.

[40] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[41] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. *International Journal of Computer Vision*, 88(2):303–338, June 2010.

[42] Giulia Pasquale, Tanis Mar, Carlo Ciliberto, Lorenzo Rosasco, and Lorenzo Natale. Enabling depth-driven visual attention on the icub humanoid robot: Instructions for use and new perspectives. *Frontiers in Robotics and AI*, 3:35, 2016.

[43] E. Maiettini, G. Pasquale, L. Rosasco, and L. Natale. Interactive data collection for deep learning object detectors on humanoid robots. In *2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids)*, pages 862–868, Nov 2017.

[44] Christopher Xie, Yu Xiang, Arsalan Mousavian, and Dieter Fox. The best of both modes: Separately leveraging rgb and depth for unseen object instance segmentation. In *Conference on robot learning*, pages 1369–1378. PMLR, 2020.

[45] Markus Suchi, Timothy Patten, David Fischinger, and Markus Vincze. Easylabel: a semi-automatic pixel-wise object annotation tool for creating robotic rgb-d datasets. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 6678–6684. IEEE, 2019.