Online Monitoring of Object Detection Performance Post-Deployment

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Abstract—Post-deployment, an object detector is expected to operate at a similar level of performance that was reported on its testing dataset. However, when deployed onboard mobile robots that operate under varying and complex environmental conditions, the detector’s performance can fluctuate and occasionally degrade severely without warning. Undetected, this can lead the robot to take unsafe and risky actions based on low-quality and unreliable object detections. We address this problem and introduce a cascaded neural network that monitors the performance of the object detector by predicting the quality of its mean average precision (mAP) on a sliding window of the input frames. The proposed cascaded network exploits the internal features from the deep neural network of the object detector. We evaluate our proposed approach using different combinations of autonomous driving datasets and object detectors.

I. INTRODUCTION

Object detection plays a vital role in many robotics and autonomous system applications. For instance, a driver-less car is expected to detect important objects such as vehicles, people and traffic signs accurately all the time. Failure to do so can cause severe consequences for the car and the people involved. Hence, there is ongoing research [1]–[10] to improve the robustness and accuracy of object detection systems. In general, an object detection system is trained and evaluated using non-overlapping training, validation, and test splits of a dataset before deployment. The underlying assumption is that the images encountered during deployment follow a similar distribution to the images presented before deployment. However, in the case of autonomous systems, the post-deployment environment can exhibit many conditions that are not well represented in the pre-deployment datasets. This leads to the fact that post-deployment performance can fluctuate and may diverge from the expected pre-deployment performance without any prior warning. Such silent change in the post-deployment performance is a serious concern for any vision-based robotic system, see Fig. 1.

The ultimate solution to meet this challenge is to develop a remarkably persistent object detection system by collecting training data from all imaginable conditions that can be encountered post-deployment. As such a solution is not practical, one remedy to this situation is to deploy a performance monitoring system for the object detector that can raise warnings when the performance drops below a critical threshold.

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Fig. 1: The performance of an object detector deployed on a self-driving car depends heavily on the environmental conditions, such as traffic density, road type, and time of day. The mAP (calculated over a sliding window of 10 frames) even fluctuates significantly within each scenario. We show that a specialised performance monitoring network can predict the mAP of the object detector to inform downstream tasks of its expected reliability. In this figure, the first row shows the fluctuating mAP of three road scenes (motorway day, city day and night). The second row shows one sample image from each road scene.

A performance monitoring system is expected to provide the capability of self-assessment to the object detector. This self-assessment can improve safety and robustness post-deployment by monitoring the performance continuously and allowing to take preventive measures when the performance seems lower than expected.

To this end, the contribution of this paper is a novel cascaded neural network that exploits the internal feature maps from the deep neural network of the object detector for the task of online performance monitoring. Our proposed cascaded network operates on a sliding window of frames and continuously predicts the performance of the object detector in terms of mean average precision (mAP). We evaluate our proposed approach against multiple baselines using different combinations of datasets and object detection networks.

The rest of the paper is organized as follows: In Section II we review the related works on performance monitoring. In Section III we introduce our method for online performance monitoring.
monitoring of object detection post-deployment. Section IV outlines our experimental setup. Section V presents the results and finally in Section VI we draw conclusion for this work.

II. RELATED WORKS

Self-assessment and performance monitoring in robotics applications is an important capability due to the high requirements of safety and robustness. In [11], a framework called robotic introspection is developed to provide self-assessment mechanism for field robots during exploration and mapping of subterranean environments. Later [12] and [13] extended this work for obstacle avoidance and semantic mapping assessment. These works examine the output of the underlying models to predict their expected performance.

Another approach to address the performance monitoring problem is to evaluate model input before inference. [14] proposed a framework following this paradigm. They train an alert module to find cases where the target model will fail. Later, a similar approach was used for failure prediction for MAV [15], hardness predictor [16] for image classifiers and probabilistic performance monitoring for robot perception system [17] for the task of pedestrian detection based on past experience from repeated visits to the same location.

Exploiting model confidence and uncertainty is another line of research to monitor the performance of a target model. Trust score [18], maximum class probability [19] and true class probability [20] are some recent works based on model confidence to identify the failure of an underlying image classifier. In the context of uncertainty estimation, [21] proposed to use dropout as a Bayesian approximation technique to represent model uncertainty. Later, [22], [23] applied this idea to identify the quality of image and video segmentation network.

In the object detection context, there are few works which address the performance monitoring to some extent. [24] and [25] use dropout sampling and hard false positive mining respectively to identify object detection failures. [26] and [27] use internal and hand-crafted features of an object detector respectively to identify false negative instances during deployment. These works focus on a per-object and per-frame basis and do not provide an overall assessment of the object detector performance considering the combined aspects of false positives, false negatives and object localization accuracy. These aspects are captured by a summary metric such as mAP. Our proposed approach can monitor object detection performance online by predicting the quality of its mAP for a sequence of images during the deployment phase without using any ground-truth data.

III. APPROACH OVERVIEW

In this section, we present our approach to online monitoring of object detection performance during the deployment phase. We start by formalizing the problem, and then we describe our proposed cascaded neural network architecture that operates on the feature stream generated by the underlying object detection network to monitor its performance in real-time.

Let us denote an object detection network as $od_{net}$ that is mounted on a driver-less car to detect object of interest like vehicle and pedestrian from the road. It takes a continuous stream of images $I = \{I_1, I_2, \ldots, I_N\}$ and detect all possible objects from each $I_i$. Our goal is to monitor the performance of $od_{net}$ by predicting its mAP continuously over a sliding window of images.

As described by [28], modern deep CNN’s become unstable when the input image is translated, rescaled or slightly transformed by any other means. This observation holds for object detector deployed on a driver-less car too, where the mAP between two consecutive frames might vary significantly because of irrelevant or negligible changes in the viewpoint. As a result, per-frame performance monitoring can raise unnecessary false alarms. To mitigate this issue, we are adopting per sliding window performance monitoring, where the mAP between two consecutive windows does not change drastically. Hence, the performance monitoring network is expected to produce a consistent prediction by examining a sequence of images. To achieve this, we will deploy a second convolutional neural network that will access the internal features of $od_{net}$ to predict the quality of the mAP for each sliding window of images. This second network will be referred as performance monitoring network, $pm_{net}$.

Instead of processing each input image $I_i$ like $od_{net}$ does at a time, $pm_{net}$ operates on a sequential images and predict the overall mAP of $od_{net}$ on these images. We will use $\omega$ to refer the window size used by $pm_{net}$. Here, $pm_{net}$ takes a stream of windows $W = \{W_1, W_2, \ldots, W_M\}$ and monitor the performance for each $W_i$, where $W_i = \{I_i, I_{i+1}, \ldots, I_{i+w}\}$.

We formulate the task of performance monitoring as a multi-class classification problem consisting of $C$ classes. To do so, the per-window mAP range is split into $C$ equal and consecutive parts and labeled from 0 to $C-1$. We will denote these per-window mAP label using $mAP_w$. The lowest and the highest label, 0 and $C-1$ refer to the worst and the best possible classes respectively. As there is an ordinal relation among these labels, we will consider this multi-class classification problem as ordinal classification [29].

Our proposed $pm_{net}$ exploits the features generated by $od_{net}$ during per frame inference. $od_{net}$ uses a backbone architecture $B$ to extract features for the inference task where $B$ is a collection of interconnected convolutional layers. During the inference, for each image $I_i$, $B$ generates a set of $p$ feature maps, $L_i = \{L_{i1}, L_{i2}, \ldots, L_{ip}\}$. Here, shape of $L_{ij}$ is $c_{ij} \times h_{ij} \times w_{ij}$; $c_{ij}$, $w_{ij}$ and $h_{ij}$ are the channel, width and height of the $j^{th}$ convolutional layer of the $i^{th}$ image.

After each inference $pm_{net}$ extracts $L_i$ from $B$ for input $I_i$ and apply channel-wise average pooling to convert each 3D features into 2D. Now the converted set of feature is $\tilde{L}_i = \{\tilde{L}_{i1}, \tilde{L}_{i2}, \ldots, \tilde{L}_{ip}\}$ and shape of $\tilde{L}_{ij}$ is $1 \times h_{ij} \times w_{ij}$. These operations are performed for all $I_i$ and the newly formed
corresponding 2D features are stacked together in channel-wise direction. That means the $\hat{L}_{i+1,j}$ is stacked with $\hat{L}_{ij}$. After processing $\omega$ images we get feature $F_{W_i}$ for $W_i$. Here $F_{W_i} = \{F_1, F_2, \ldots, F_p\}$ and $F_i$ has the size of $\omega \times h_{ij} \times w_{ij}$. The task of pm$_{net}$ is to predict mAP$_w$ from $F_{W_i}$.

We design the pm$_{net}$ as a cascaded convolutional neural network to train it to predict mAP$_w$ from $F_{W_i}$. Here, each layer of pm$_{net}$ is implicitly connected with all the previous layers through their individual convolutional filter. Using this network, we exploit the rich multi-level semantic features generated by the od$_{net}$ instead of only using the last convolutional layer features. pm$_{net}$ uses a set of convolutional filter $f = \{f_1, f_2, \ldots, f_{p-1}\}$ to propagate the features of $F_{W_i}$ from one layer to the next. Each filter $f_i$ operates on $F_i$ to generate a new feature $\tilde{F}_i$ which has the same shape of $F_{i+1}$. Now a concatenation is performed to join $\tilde{F}_i$ and $F_{i+1}$ in channel-wise direction. This set of operation can be formulated using Equation 1

$$\mathcal{F} = f_i(F_i) \oplus F_{i+1}; \quad i = 1, 2, \ldots, p - 1 \quad (1)$$

Next, we apply adaptive average pooling operation on $\mathcal{F}$ to generate a one dimensional feature vector. This feature is passed through subsequent fully connected layers to generate the final prediction for $F_{W_i}$. See Fig. 2 for a visualisation of these procedures.

**IV. EXPERIMENTAL SETUP**

In this section we will describe the settings that we used to evaluate our proposed approach.

**A. Experimental Steps**

We can describe the overall experimental procedure using three steps. At first an object detector is trained using transfer learning technique to detect different objects (vehicle, pedestrian) from a dataset named as primary training dataset. In the next step, the detector is used to detect the similar objects from another dataset (secondary training dataset) which was not used during the initial training phase. This secondary training dataset consists of stream of images. In this step, a sequential stream of images is fed to the object detector and for each consecutive window of images we collect the features for each window and calculate the corresponding mAP using the secondary training dataset as groundtruth. Then, we train the proposed cascaded CNN, pm$_{net}$ to predict the mAP from the collected per-window features. Next, we use multiple metrics and another image stream dataset (test dataset) unused in previous steps to evaluate the proposed approach. See Fig. 3 for a high-level overview of these steps.

**B. Dataset**

We used multiple combination of three different datasets (KITTI [30], BDD [31], Waymo [32]) to conduct all the experiments. In each settings, one dataset from KITTI and BDD has been used as primary training dataset. Then we used one of the video datasets from KITTI, BDD and Waymo as the secondary training dataset which was not a part of primary training dataset. To evaluate the system we used one video dataset that was unused as primary training dataset or secondary training dataset.

**C. Training**

We trained two-stage Faster RCNN [2] and one-stage RetinaNet [33] object detection networks pre-trained on MS-COCO [34] dataset to detect vehicle and pedestrian from the KITTI and BDD dataset. Both of these networks use ResNet50 [35] as their backbone. To be interoperable among multiple datasets, classes like car, van, tram and bus have been assigned to vehicle class. Besides, pedestrian and person classes from all the datasets are denoted as pedestrian class. Moreover, objects less than 25 pixel in width or height are removed from all the datasets. To generalize the object detection and performance monitoring network training, we applied several weather related augmentation (random fog, snow and rain). Table 1 shows the object detection accuracy in mAP for primary training dataset and object detection network settings.

We adopted the CORAL [36] framework that uses a set of binary classifier to train pm$_{net}$ as an ordinal classifier.

**TABLE I: Object detection accuracy in mAP for FRCNN and RetinaNet network on KITTI and BDD100K dataset for detecting vehicle and pedestrian.**

| Model       | KITTI  | BDD     |
|-------------|--------|---------|
| FRCNN       | 66.0%  | 52.4%   |
| RetinaNet   | 60.58% | 65.49%  |
Each binary classifier predicts whether per-window mAP is within a particular range. This prediction is controlled by a decision threshold. The ordinal classifier has 5 classes from 0 to 4 each incrementally spanning 0.2 per-window mAP. In this case, class 2 is equivalent per-window mAP below 0.4.

To train the \( pm_{\text{net}} \), we used the Adam optimizer [37] and an initial learning rate of 0.001 with batch size 32.

For all of the following experiments, we use a sliding window of 10 frames. We empirically found that this value provides a balance between the high sensitivity of smaller windows and the smoothing effect of large windows as shown in Fig. 4.

D. Evaluation Metrics

We used mean absolute error (MAE), root mean squared error (RMSE) and zero-one error (ZOE) [38], which is the fraction of incorrect classification, as the evaluation metric for \( pm_{\text{net}} \) ordinal classification task. To compare with the baselines and to evaluate how well the \( pm_{\text{net}} \) can detect critical mAP label we used true positive rate at 5% false positive rate (TPR@FPR5) , false positive rate at 95% true positive rate (FPR@TPR95) and area under the ROC curve (AUROC) metric.

E. Baseline Approaches

Baseline 1: In [27], Ramanagopal et. al. proposed an approach to identify perception failure of an object detection system. They used manually selected features like bounding box confidence and their mean and median overlap to identify false negative instances generated by an object detector. Following their approach, in this baseline we extract a set of features from each image after performing the object detection. This set includes mean and median of all detected bounding box confidences, mean and median overlap, width and height of all detected bounding boxes in normalized scale. We extracted these features from all images of each window and concatenated them together to generate a one dimensional feature corresponding the window. Next, each mAP per-window is converted into a binary label using a critical threshold 0.4. Any mAP which is lower than this threshold is assigned to positive class otherwise negative. Next we train a fully connected binary classifier to predict the probability of each window to be assigned in the positive or negative class.

Baseline 2: In this baseline we are using internal features from the last convolutional layer of a trained object detector backbone instead of hand crafted features. After each inference, we collect the 3D features from the last backbone layer and apply the average pooling technique to convert that 3D features into 1D. After concatenating all 1D features from all images of a window, we get a feature corresponding to that window. Using the critical threshold discussed in baseline 1, we assign each window into positive and negative classes. Then a fully connected binary classifier is trained to predict these classes from the window feature.

We use class 2 which is equivalent to critical threshold 0.4
Using features collected from RetinaNet backbone.

In this section, firstly, we summarize how well the proposed performance monitoring network works as an ordinal classifier. Secondly, we evaluate the accuracy of the proposed network to detect when per-window mAP drops below the critical threshold of 0.4.

**Experiment 1:** Table II shows the \( pm_{\text{net}} \) ordinal classification accuracy using MAE, RMSE and ZOE error metric for four different dataset settings. Here, \( od_{\text{net}} \) is trained using FRCNN and \( pm_{\text{net}} \) is trained and evaluated using FRCNN backbone features. The second row shows \( pm_{\text{net}} \) error metric for ordinally classifying classifier based baselines.

Table III presents \( pm_{\text{net}} \) error metric for similar dataset settings as Table II. Here, \( od_{\text{net}} \) is trained using RetinaNet object detection network and \( pm_{\text{net}} \) is trained and evaluated using RetinaNet backbone features. In this table, primary training dataset BDD, secondary training dataset Waymo and test dataset KITTI demonstrates the lowest error than other dataset settings. This observation is consistent with Table II and suggests that the large diversity of BDD and Waymo dataset are effective for the performance monitoring of \( pm_{\text{net}} \) in the KITTI dataset.

**Experiment 2:** This experiment compares the proposed performance monitoring network with the baselines.

During the \( pm_{\text{net}} \) evaluation, the decision threshold is varied from 0 to 1 to produce the 5 class ordinal prediction for each threshold. Then using the critical threshold the ordinal class prediction is converted to a binary prediction to compute the TPR and FPR. Therefore, each decision threshold generates a pair of TPR, FPR and using these metrics we calculate the TPR@FPR5, FPR@TPR95 and AUROC for our proposed approach.

As the two baselines use binary classifier approach, we can use their predicted positive class probability and corresponding groundtruth to calculate the TPR@FPR5, FPR@TPR95 and AUROC metric.

Table IV shows the comparison between \( pm_{\text{net}} \) and the two baselines using multiple metrics. For this table, the \( od_{\text{net}} \) is trained using FRCNN and the \( pm_{\text{net}} \) is trained and evaluated using FRCNN backbone features. In terms of TPR@FPR5, \( pm_{\text{net}} \) outperforms both of the baselines by a large margin. While the maximum TPR@FPR5 for \( pm_{\text{net}} \) over four dataset settings is 0.922, baseline 1 and 2 reach at maximum 0.214 and 0.513 respectively. For FPR@TPR95 the minimum score for our proposed approach is 0.054. However, the minimum FPR@TPR95 for baseline 1 and 2 is 0.707 and 0.457 respectively. In AUROC metrics, \( pm_{\text{net}} \) performs better than the baselines by obtaining 0.929 while the maximum AUROC of both baselines is 0.610. Although we have referred only the maximum score of each individual metrics from the four dataset settings, our proposed approach outperforms the baselines in all metrics and dataset settings.

**V. Evaluation and Results**

Consequently, classes from 0 to 1 and 2 to 4 are assigned to positive and negative classes respectively. This conversion allows to compare our ordinal classifier with the binary classifier based baselines.
Table [X] represents the comparative accuracy among \( pm_{\text{net}} \) and two other baselines. Here, the underlying object detector is trained using RetinaNet network and the corresponding performance monitoring network is trained and evaluated using features collected from RetinaNet backbone. In this case, for TPR@FPR5 metric, the maximum score that our proposed approach achieves out of four dataset settings is 0.953 while the maximum of two baselines among this four settings is 0.708. In case of FPT@TPR95 and AUROC, our proposed approach outperforms both of the baselines by a large margin.

Experiment 3: In order to monitor object detection performance online we are required to simultaneously use the performance monitoring network along with the object detection system. Hence, the inference time and GPU memory requirement of \( pm_{\text{net}} \) should be minimal for practical usage. On average \( pm_{\text{net}} \) and \( od_{\text{net}} \) inference time is \( 3.34 \pm 0.126 \) ms and \( 28.11 \pm 0.404 \) ms in our TITAN V GPU workstation. Besides, \( pm_{\text{net}} \) uses 243 MB of GPU memory which is 20.81% of memory used by the \( od_{\text{net}} \).

VI. CONCLUSION

As deep learning-based object detection become essential components of a wide variety of robotic systems, the ability to continuously assess and monitor their performance during the deployment phase become critical to ensure the safety and reliability of the whole system. In this paper, we proposed a specialised performance monitoring network that can predict the quality of the mAP of the object detector, which can be used to inform downstream components in the robotic system about the expected object detection reliability. We show the effectiveness of our approach using a combination of different autonomous driving datasets and object detectors.

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