Extending Recognition in a Changing Environment

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Abstract: We consider the task of visual recognition of objects and their parts in a dynamic environment, where the appearances, as well as the relative positions between parts, change over time. We start with a model of an object class learned from a limited set of view directions (such as side views of cars or airplanes). The algorithm is then given a video input which contains the object moving and changing its viewing direction. Our aim is to reliably detect the object as it changes beyond its known views, and use the dynamically changing views to extend the initial object model. To achieve this goal, we construct an object model at each time instant by combining two sources: consistency with the measured optical flow, together with similarity to the object model at an earlier time. We introduce a simple new way of updating the object model dynamically by combining approximate nearest neighbors search with kernel density estimation. Unlike tracking-by-detection methods that focus on tracking a specific object over time, we demonstrate how the proposed method can be used for learning, by extending the initial generic object model to cope with novel viewing directions, without further supervision. The results show that the adaptive combination of the initial model with even a single video sequence already provides useful generalization of the class model to novel views.

1 INTRODUCTION

The world around us is a dynamic environment, and a robust visual recognition system should therefore be able to detect and interpret objects as they change over time. The dynamic changes are useful, since they provide cues for both segmentation and 3D structure, but also challenging, as both the appearance and the relative positions of visual features may change over time. A recognition system should be able to learn the multiple appearances and structures of a class of objects from a dynamic input, and ideally accomplish this with little or no supervision that provides labeling of the objects and their parts.

In this paper we deal with a specific aspect of dynamic recognition. We assume an initial model that can detect an object and its parts from a limited set of views (such as side views of cars or airplanes). Given an input video, the model successfully detects the object and its parts at some time t_0. The goal is to continue to detect the object as its images changes in the video at later times $t > t_0$, and to use the dynamically changing views to extend the model and allow it to classify novel objects under new views which the original model fails to recognize. We describe a learning process that can efficiently combine the initial model with the novel dynamic input and obtain a significant extension of the original model based on even a single object instance, as illustrated in figure 1.

A main contribution of our approach is constructing the object model at time $t > t_0$ by combining two sources of information: compatibility with the measured optical flow and similarity to the object model at an earlier time.

2 RELATED WORK

We follow the paradigm of detecting and localizing objects by their constituent parts. Part-based object recognition has been successfully demonstrated in many recognition problems, mainly for detecting objects in static images (Agarwal et al., 2004; Crandall et al., 2005; Epshtein and Ullman, 2007; Felzenszwalb and Huttenlocher, 2005; Fergus et al., 2005). Object parts can be obtained manually (Felzenszwalb and Huttenlocher, 2005) or automatically (Agarwal et al., 2004; Ullman et al., 2002) during training from a set of sample images of the object. Each part is characterized by a visual

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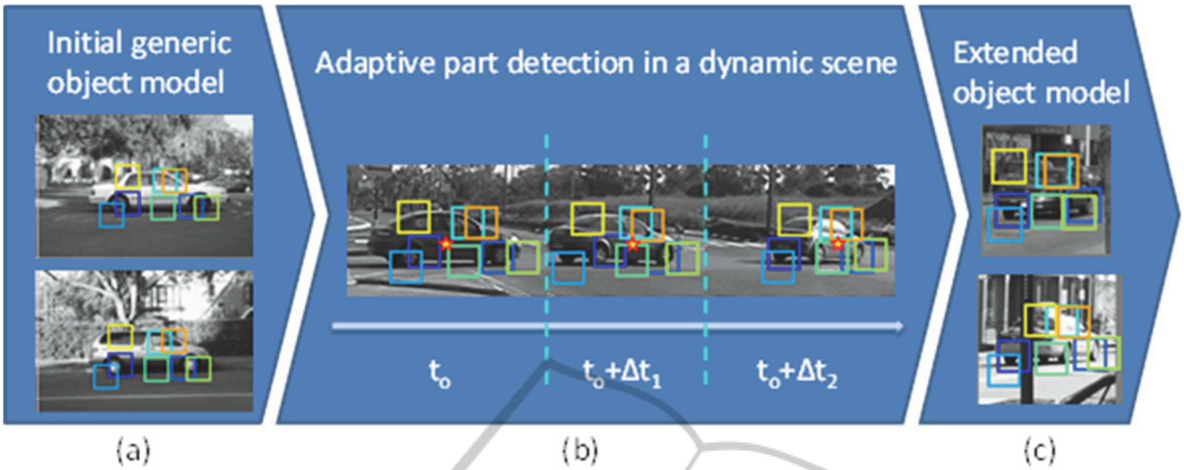


Figure 1: Approach outline. Given an initial generic model of the class object in a certain view (a), an object instance and its parts are detected in a dynamic scene at some time t_0. The model continues to detect the parts for as long as possible, while adapting to novel views of the object at times $t > t_0$ (b). The updated model is extended to cope also with general class object instances in novel views without external supervision (c).

appearance and by relations relative to other object parts. (Felzenszwalb and Huttenlocher, 2005) have suggested a pictorial structure representation using a collection of parts arranged in a deformable configuration. They model the appearance of each part separately, and represent the deformable configuration with spring-like connections between pairs of parts. (Crandall et al., 2005) have extended this approach by introducing a class of statistical models for part-based object recognition that are explicitly parameterized according to the degree of spatial structure they can represent. These models, called k-fans, provide a way of relating different spatial priors that have been used for recognizing generic classes of objects, including joint Gaussian models and tree-structured models. (Felzenszwalb et al., 2010) combined the powerful histogram of gradients (HoG) features of (Dalal and Triggs, 2005) into the part-based recognition framework. Their approach uses a star-structured part-based model consisting of HoG filters (representing the object "root" and constituent parts), and associated deformation models. To cope with multiple views the algorithm splits the training set and learns a mixture of models, each corresponding with a different view. In this learning process the number of models (views) should be manually defined, and the training set should consist of enough samples for each view.

Object and part detections were also considered when applied to dynamic visual input, mainly for tracking. (Dalal et al., 2006) have combined differential optical flow descriptors with their holistic object HoG descriptors for the task of detecting and tracking humans in video sequences. However, appearance and motion features are learned only during training and cannot be updated to cope with novel appearances and motion when observed. (Ramanan et al., 2007) suggested to learn specific appearance models of class objects from detections of a generic model in the input video sequence. These models are then used to track the object instances in the analyzed video. However, this approach is not suitable for online adaption of the model to the input dynamics.

Other approaches such as (Cehovin et al., 2011; Godec et al., 2011; Kwon and Lee, 2009; Lim et al., 2005) introduce online learning and model adaption under the tracking-by-detection paradigm for robust object tracking under heavy deformations and occlusions. These approaches maintain a specific object model of the tracked object, while adapting to changes in the object appearance and geometry throughout the tracking period. However, as the target goal of these methods is tracking of a specific object instance, they do not aim to generalize to other class object instances, or maintain past object configurations over time. Recently, (Kalal et al., 2011) have suggested a system for long-term tracking of a human face in unconstrained videos. The system is built on tracking-learning-detecting approach using an off-line trained generic detector and an online trained validation mechanism for pruning incorrect detections. A multi-view model of the target is automatically learned from a single frontal example and the unlabeled dynamic visual input. Nevertheless, although past configurations of the tracked object are maintained over time, the model does not generalize to other class object instances, as it is still targeted toward tracking.

In this paper we present an adaptive parts detection model for a dynamic environment, that can provide a recognition system with a simple and efficient unsupervised learning mechanism that updates the model over time. The suggested scheme is a natural extension of state-of-the-art part detection methods in static images. Our scheme combines the structure of the model at time t with the optical flow between time t and $(\mathrm{t}+\Delta\mathrm{t})$. Using both motion and spatiotemporal consistency, the model adapts online to dynamic changes of the observed object, both appearance and structure. Using statistical kernel density estimation (KDE) and approximate nearest neighbors (ANN) tools, our model provides a simple and efficient mechanism for extending a generic object model to cope with novel object views, via adaption to dynamic visual input and without external supervision. The rest of this paper is organized as follows: in section 3 we describe the model and our probabilistic framework; in section 4 we present an experimental performance study; and in section 5 we discuss and conclude our insights from this work.

3 METHODS

3.1 Overview

The adaptive model is initially a static, single-image parts detection model of an object class (such as cars or airplanes), with a star-like geometric structure similar to (Crandall et al., 2005; Epshtein & Ullman, 2007; Felzenszwalb et al., 2010; Fergus et al., 2005). This model is learned from a limited set of view directions (such as side views). When applied to video sequences, the model acts as a standard static classifier on each frame until an instance of the object class is successfully detected at frame t_0. The model is then applied to every two consecutive image frames t and $(\mathrm{t}+\Delta\mathrm{t})$ of the video sequence, as long as the object is reliably detected.

Parts interpretation (identity and location) at time $(\mathrm{t}+\Delta\mathrm{t})$ is obtained by combining two sources: the model $\mathrm{M}(\mathrm{t})$ at time t, and the optical flow between the frames. The model is then updated to $\mathrm{M}(\mathrm{t}+\Delta\mathrm{t})$ to be used in the subsequent frame. The updated model at each frame is an adapted instance of the initial model, based on the two corresponding views. We utilize adaptive ANN search, combined with statistical KDE, for efficient online updating of the model, using the dynamically changing views to extend the initial object model as described below.

3.2 Probabilistic Model

The initial static object detector is based on the representation of the object and its constituent parts following (Epshtein and Ullman, 2007), with a graphical model similar to the one shown in figure 2, excluding spatiotemporal variables. The appearances of parts and their geometric configurations are learned from positive static image samples which contain the class object (one instance roughly centered in the image) and negative image samples which do not contain the class object. The learning process may be in a fully supervised manner. However, we prefer the weakly supervised learning approach of object parts (Agarwal et al., 2004) which is more realistic, and automatically selects the parts from a large set of image fragments according to their mutual information with the object class (Vidal-Naquet and Ullman, 2003). For each selected part, a set of appearances of equivalent parts together with their geometric configuration (relative offset from the object center in our settings) is extracted from the positive training images by similarity matching.

The probabilistic framework of the adaptive spatiotemporal model is a natural extension of the initial static object detector and is defined as follows. At time frame $(\mathrm{t}+\Delta\mathrm{t})$ we define a random variable C to represent the object center location in the image, and a set of random variables denoted by $\{\mathrm{X}\}=\{\mathrm{X}_\mathrm{i}\}_{\mathrm{i}=1}^{\mathrm{N}}$ to represent the image locations of N object parts. The observed appearances of object parts in the image are represented by a set of random variables, which are image feature descriptors $\{\mathrm{F}\}=\{\mathrm{F}_\mathrm{i}\}_{\mathrm{i}=1}^{\mathrm{N}}$. The image locations of the interpreted object and parts in the previous frame t are represented by the random variables C^p and $\{\mathrm{X}^\mathrm{p}\}=\{\mathrm{X}_\mathrm{i}^\mathrm{p}\}_{\mathrm{i}=1}^{\mathrm{N}}$ respectively. The observed velocities of the object and parts are derived from the optical flow between frame t and $(\mathrm{t}+\Delta\mathrm{t})$, and are represented by the random variables V_c and $\{\mathrm{V}\}=\{\mathrm{V}_\mathrm{i}\}_{\mathrm{i}=1}^{\mathrm{N}}$ respectively. The representation can be described by the graphical model shown in figure 2. The full interpretation of object and parts at frame $(\mathrm{t}+\Delta\mathrm{t})$ is given by the joint probability as in equation 1.

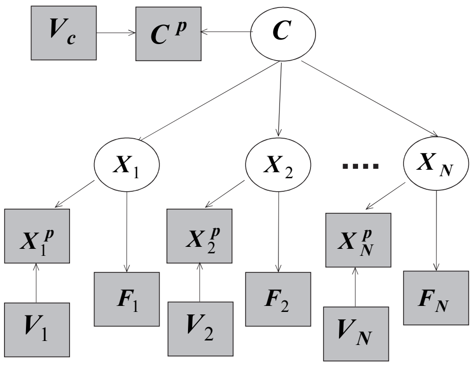


Figure 2: Probabilistic graphical representation of the adaptive model. Similar to the initial static model, the latent variables C and {X} represent the image locations of the object and its parts in the current frame. The observed appearance of the parts in the current frame is represented by {F} which are image features. Spatiotemporal information is represented by observed image positions of the object and its parts at the previous frame C^p and $\{X^p\}$ respectively, and their measured velocities V_c and {V} respectively (derived from the optical flow between the frames).

$$P(C,\{X\},\{F\},V_c,\{V\},C^p,\{X^p\}) = P(C)\cdot P(V_c)\cdot P(C^p/C,V_c)\cdot \prod_{i=1}^{N} P(X_i/C)\cdot P(V_i)\cdot P(X_i^p/X_i,V_i)\cdot P(F_i/X_i) \quad (1)$$

$\mathbf{P(F_i/X_i)}$: We use a non-parametric representation for the probability $P(F_i/X_i)$ of the observed appearance of an object part i conditioned on its image location. For given image positions, we use SIFT descriptors (Lowe, 2004) as appearance features of the image patches centered at these positions. Given a set of appearance features for part i, the probability of a new appearance feature F_i is obtained using a Gaussian KDE over the L_2 distances of F_i from a subset of k nearest neighbors (k-NN) $\{Y\} = \{Y^j\}_{j=1}^{k}$ among the original set as shown in equation 2. For efficiency we use approximate nearest neighbors search as in (Arya & Mount, 1993).

$$P(F_i/X_i) \approx \frac{1}{\sqrt{2\pi}hk}\cdot\sum_{j=1}^{k}\exp\left(-\frac{\|F_i - Y^j\|}{2h^2}\right) \quad (2)$$

Using this non-parametric representation for the conditional probability of observed appearances, allows us to control the online adaption of the appearance model, by changing the set of known appearances at each time frame as follows. At the update phase of the two-frame scheme, the appearance of the successfully interpreted object part i at the previous frame, is added to the current set of known appearances of this part, thus allowing a gradual adjustment of the appearance model via the k-NN approach. Furthermore, by memorizing previously observed appearances of the object part, this approach provides a robust online adaption mechanism which can recover from possible erroneous interpretations. Based on initial experiments, we manually determined the number of nearest neighbors ($k = 25$) and the bandwidth parameter ($h = 0.27$), which remain the same in all our experiments.

$\mathbf{P(X_i/C)}$: The structure of object parts is represented as a geometric star-like model. The probability $P(X_i/C)$ of an object part i conditioned on the object center location is modeled as a mixture of Gaussians. The first component is the geometric configuration of the initial static object detector for part i, represented by a Gaussian distribution over spatial offsets between the object center locations and part locations (in the training set images). The second component is a Gaussian kernel over spatial offsets between recently interpreted object and part locations in the input video, which are being updated online during the update phase of the two-frame scheme. (We used the 3 most recent interpretations in our experiments.) The weights of the mixture components may be adjusted according to the interpretation confidence levels. However, in our experiments we used constant uniform mixing weights.

$\mathbf{P(C^p/C,V_c)}$, $\mathbf{P(X_i^p/X_i,V_i)}$: Spatiotemporal consistency and motion constraints for the object and parts between two time frames, are represented via the conditional probabilities $P(C^p/C,V_c)$ and $P(X_i^p/X_i,V_i)$ respectively. For every two time frames we calculate the velocity of the whole object and interpreted part i at the previous frame t. These velocities are calculated as a weighted average of the optical flow at every pixel location within the object's and part's image regions respectively, utilizing a dense optical flow algorithm (Black & Anandan, 1996). The velocities imply Gaussian distributions for the location of the object and part at the current time frame $(t + \Delta t)$ given their interpreted locations at the previous frame t (equation 3). The parameters σ_c and σ_i are set relative to the object size and part size respectively (we used a factor of 0.5 in our experiments).

Figure 3: Image samples from the image and video datasets. (a,b) Training images of the initial model of side-view cars and airplanes (Fei-Fei *et al.*, 2007; Fergus *et al.*, 2003). (c,d) Video sequences of cars and airplanes changing their viewing directions. (e) Non-class video sequences (Ferryman, 2009). (f) Test images of cars at novel viewing directions (Cornelis *et al.*, 2006).

$$P\left(C^p / C, V_c\right) \propto \exp\left(-\frac{\left\| C - \left(C^p + \left(V_c \cdot \Delta t\right)\right)\right\|}{2\sigma_c^2}\right)$$
$$P\left(X_i^p / X_i, V_i\right) \propto \exp\left(-\frac{\left\| X_i - \left(X_i^p + \left(V_i \cdot \Delta t\right)\right)\right\|}{2\sigma_i^2}\right) \tag{3}$$

We assume uniform prior distributions for the object center among all image pixel locations $P(C)$.

4 PERFORMANCE STUDY

We demonstrate the performance of the adaptive object and parts detection model on two object categories: cars and airplanes. For each category, an initial model of the object class from a side-view is learned from a training set consisting of positive class images and negative background images. We then apply the algorithm to sets of video sequences containing instances of the class object in various dynamic environments, starting at roughly the known side viewing direction. We analyze the adaption of the model while the object and background dynamically change throughout the video sequences. Finally, we show how the updated model extends the initial model to cope with novel viewing directions of general object class instances, even after exposure to a single video sequence.

4.1 Datasets

For training initial object class models, we used 123 side-view images of cars from the Caltech101 dataset (Fei-Fei et al., 2007) to learn a car detector with 8 parts, and 473 side-view images of airplanes from Caltech dataset (Fergus et al., 2003) to learn an airplane detector with 10 parts. 467 natural images not containing the object classes were used as negative examples.

For testing the initial and the updated models, we used car images at different views from ETHZ dataset (Cornelis et al., 2006) (476 images from a side view, 154 images at roughly 30°, and 120 images at around 60°), and 103 validation images of airplanes from the Caltech dataset (Fergus et al., 2003). The models were also applied to more than 200 background images (extracted from the PASCAL'09 dataset, Everingham et al., 2009), which do not contain instances of the two object classes.

For dynamic inputs we used 3 videos of cars taken from a stationary video camera, 4 videos of airplanes from the internet, and 4 videos of people walking (not containing cars or airplanes) from (Ferryman, 2009). The car sequences, consisted of 75 frames each, and depicted 3 different cars making a left turn at a junction, starting from a side-view, and ending at a view of about $60^{\circ} - 70^{\circ}$. The airplane sequences consisted of more than 100 frames each, and depicted 4 different planes changing their viewing direction during taxi and takeoff. The walking people sequences did not contain any car or airplane instances, and were used to evaluate the classification performance of the initial and updated models. Sample images from the different image and video datasets are shown in figure 3.

To evaluate both object and parts detections in the videos, a human observer was presented with sample appearances of the class object and its parts (as learned during the training of the initial static model), and was asked to manually annotate the

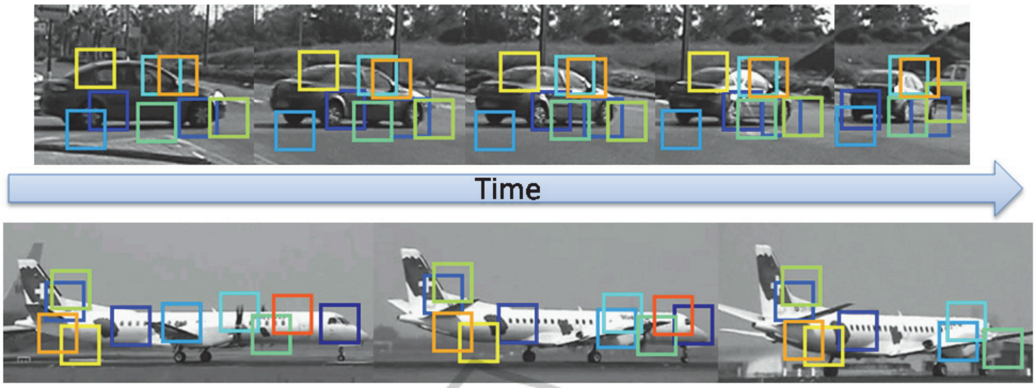


Figure 4: Examples of object parts adaption in dynamic scenes. Top: A car video sequence at frames 1, 30, 40, 50, 60. Bottom: An airplane video sequence at frames 1, 50 and 100.

positions of the object and parts at every frame of the video sequences. (It should be noted that the exact interpretation of the object and its parts during a change of view may be somewhat subjective even for human judgment.)

4.2 Adaptive Part Detection

Our algorithm first detects an object class instance in the video input based on its initial static model. We compared the performance of our initial model with a state-of-the-art object detector (Felzenszwalb et al., 2010) using the same training data of side-view images of cars and airplanes. Performance evaluation was conducted similar to the PASCAL'09 detection challenge, were detections are considered correct if the area of overlap between the predicted bounding box and ground truth bounding box exceeds 50%. Our initial model yields an average precision (AP) of 98% on the cars category and 87% on the airplanes category, compared with the detector by (Felzenszwalb et al., 2010), which yields 77% AP on cars and 97% on planes. The results demonstrate satisfying recognition capabilities of the initial model, which are comparable with state-of-the-art performance.

Once the object is reliably detected by the initial model, our model is applied to every two consecutive frames of the input video sequence, while adapting to the dynamic changes in viewing directions of the object and its parts. To evaluate the quality of the adaption process, we analyzed the localization error of the detected object and parts at each frame with respect to ground truth positions, which were manually annotated. We compared the results of the updated model with the localization error yielded by the initial static model when applied to each video frame. Table 1 shows the average localization error across changing views for a car video sequence and an airplane video sequence. For object parts of size 32×32 pixels a reasonable localization error is around 15 pixels. The table shows that the model reliably adapts to roughly 60°

Table 1: Adaptive parts detection. Object and parts average localization error and standard deviation (in pixels) across changing views in two video sequences of turning car and airplane. The analysis is performed for both the initial static model and the adaptive model. The object detection error is averaged over time frames between views, while the parts detection error is averaged also over all object parts (8 parts for the car and 10 parts for the airplane).

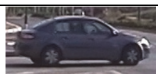
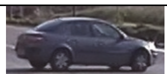
Car							
Adaptive model	Object	4±1	2±0.5	5±2	10±5	37±8	
	Parts	5±3	8±6	9±9	15±16	35±41	
Initial model	Object	3±1	4±1	6±1	43±55	136±7	
	Parts	6±3	10±9	19±16	56±50	132±46	
Airplane							
Adaptive model	Object	5±2	2±1	3±2	16±6	26±2	
	Parts	6±5	10±8	14±40	53±113	75±133	
Initial model	Object	11±2	2±2	13±2	19±9	51±22	
	Parts	6±4	8±6	20±42	57±106	84±121	

Table 2: Is a detection prior enough for successful detection? Detection performance evaluation of the initial model, when applied to 2 video sequences of the cars category. The detection threshold is reduced by a fixed rate after every successful detection, implying an increasing confidence level of finding the object at subsequent frames. Performance results are compared with the average precision rate of the adaptive model when applied to these videos.

	Detection threshold decay rate	Static model with detection prior		Adaptive model AP rate
		Precision	Recall	
Cars sequence 1	0%	100%	12.9%	71%
	1%	56.3%	20.5%	
	2%	42.9%	43.2%	
Cars sequence 2	0%	100%	26.7%	72%
	1%	95.5%	36.2%	
	2%	50.4%	53.5%	

change in viewing direction for cars and 45° for airplanes, within this localization error limit of all object parts. The initial model however, violates this localization error limit already at around 20°change from the known side-view for both object categories. The increase in performance was obtained for the whole object as well as the individual parts. Examples of parts adaption in input video sequences are shown in figure 4 for both cars and airplanes. Notably, no adaptations are made to the initial model, when the algorithm is applied to the walking people video sequences which do not contain instances of the object class.

Our online update algorithm is gradual in the sense that the adapted model combines the old and current parts appearances and object geometries. The mixture is obtained by adding the appearance and displacement from the current model to the ANN structure. We compared this mixed adaptation with an alternative where the current-frame model (appearance and geometry of the detected object) completely replaces the previous model. The evaluation for the detection performance of the object and parts was done on a car video sequence. Our adaptive algorithm yielded 70% AP for the detection of the whole object and 60% AP for the detection of the individual parts. The replacement alternative yielded 58% AP for the detection of the whole object, but only 40% AP for the detection of the parts, which is similar to the performance of the initial static model of 44% AP for the object detection and 39% AP for the parts detection. These results demonstrates the benefit of using a mixture of the initial model with the novel input, even in dealing with views not included in the original model.

As temporal consistency of the dynamic visual input is an important source of information for the recognition process, it may be argued that a static object model alone may suffice, if we increase the prior for detecting the object after each successful detection. To examine this possibility, we evaluated the detection of the static object detector on test video sets, while decreasing the initial detection threshold by a fixed rate after each frame when the object was successfully detected. Table 2 shows the evaluation results for 2 video sets of the cars category. We used threshold decreasing rates of 1% and 2%, and compared the performance with a non-decreasing (0%) threshold. The initial threshold was obtained at equal precision-recall rates of the static object detector during training. As the threshold decreasing rate goes up, recall rates increase as well, but precision drops rapidly, and the overall performance is inferior to the adaptive model.

4.3 Learning New Views

Our algorithm, when applied to dynamic visual input, adapts to changes in viewing directions of the object and extends the initial model to cope with novel views of the class object. In this experiment we show that the adaptive combination of the initial model with even a single video sequence already provides useful generalization of the class model to novel views. To evaluate the detection performance of the updated model, we tested the car model that was adapted to a turning car, on a set of car images seen from 3 different views: a side-view, roughly 30° view and about 60° view (Cornelis et al., 2006). Each image contains a different car instance, none of which was already observed by the model (neither during the training of the initial model, nor in the video sequences). For comparison, we also tested a state-of-the-art object detector by (Felzenszwalb et al., 2010), that was trained on side-view car images. The results in figure 5 show that the updated model generalizes to the new viewing directions of 30° and 60° without losing the performance on the initial side-view. Example part detections images are shown in figure 6.

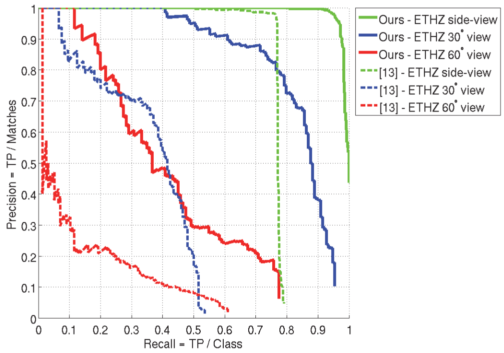


Figure 5: Learning novel views. Object detection precision-recall graphs for different views of cars. Shown in solid is the detection performance of our adaptive model after it was applied to a single video sequence of a turning car. The colors indicate the 3 views of car images from the ETHZ dataset (Cornelis *et al.*, 2006) at side-view, 30° and 60°. The results show that the adapted model generalizes to the new views with high precision rates, while maintaining high precision-recall rates for the initial side-view. Dashed lines indicate for comparison the performance of a state-of-the-art detector by (Felzenszwalb *et al.*, 2010) trained on side-view car images.

5 DISCUSSION

This paper presents an approach to adaptive object and parts detection in a dynamic environment. Starting with an initial model of an object class covering a limited set of views, our algorithm is applied to a video input which contains the object moving and changing its viewing direction. Once the object is detected at some time t_0, the goal is to continue to detect the object as its images change in the video at later times $t > t_0$, and to use the dynamically changing views to extend the model, and allow it to classify novel objects under new views, which the initial model fails to recognize. The dynamic changes are challenging, since both the appearance of object parts as well as their relative positions may change considerably over time.

We combine two sources of information in constructing the object model at time $(t + \Delta t)$: compatibility with the measured optical flow between time frame t and $(t + \Delta t)$, and similarity to the object model at time t. These sources of dynamic visual information are well studied in human vision and known as motion and spatiotemporal consistency. Our approach also provides a simple general method of dynamically updating an object model: by combining approximate nearest neighbors search with kernel density estimation, the model update is obtained by an adaptive mixture of old and new instances, which allows efficient gradual adaption to the changing appearance and structure.

Unlike tracking-by-detection methods, which focus on the tracking of a specific object target over time rather than building a general class model, the results demonstrate how the proposed method can be used for learning, by extending an initial generic object model, to cope with a new set of viewing directions of the object class, without further supervision. The results show that the adaptive combination of the initial model with even a single video sequence already provides useful generalization of the class model to novel views.

While current state-of-the-art methods such as (Felzenszwalb et al., 2010) learn multiple configurations of an object class from a set of limited viewing directions in a supervised manner, the suggested approach allows the automatic acquisition of novel views, by extending known configurations via adaptive parts detection in dynamic scenes. The adaption is incremental and the model is updated with every new input. A future extension of the current work could be to use a large set of videos to automatically construct a final model that covers a large set of viewing directions.

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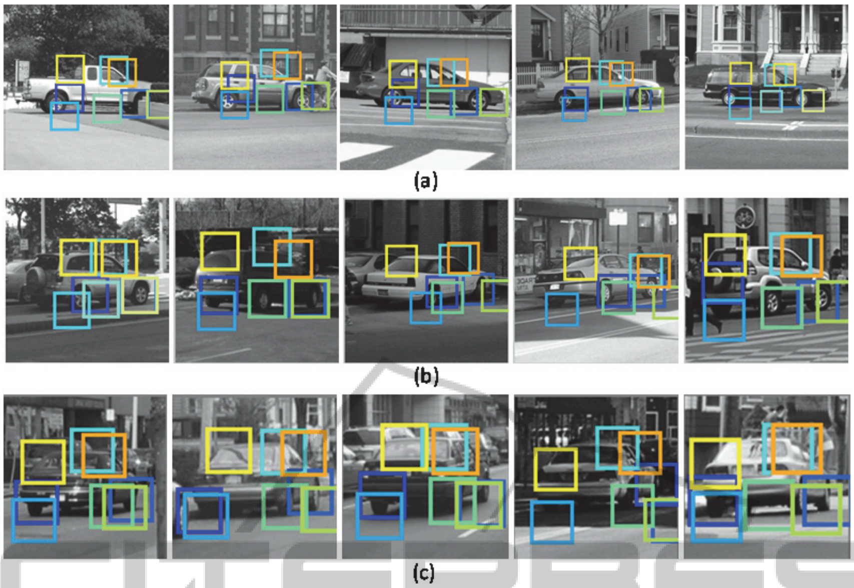

Figure 6: Parts detection examples of the adaptive model after it was applied to a single video sequence of a turning car. Car images are from the ETHZ dataset (Cornelis et al., 2006): (a) at side-view, (b) at 30° view, (c) at around 60° view.

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