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Efficient Boosting-Based Active Learning for Specific Object Detection Problems

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***Abstract*—In this work, we present a novel active learning approach for learning a visual object detection system. Our system is composed of an active learning mechanism as wrapper around a sub-algorithm which implement an online boosting-based learning object detector. In the core is a combination of a bootstrap procedure and a semi automatic learning process based on the online boosting procedure. The idea is to exploit the availability of classifier during learning to automatically label training samples and increasingly improves the classifier. This addresses the issue of reducing labeling effort meanwhile obtain better performance. In addition, we propose a verification process for further improvement of the classifier. The idea is to allow re-update on seen data during learning for stabilizing the detector. The main contribution of this empirical study is a demonstration that active learning based on an online boosting approach trained in this manner can achieve results comparable or even outperform a framework trained in conventional manner using much more labeling effort. Empirical experiments on challenging data set for specific object deteciton problems show the effectiveness of our approach.

***Keywords*—Computer vision, object detection, online boosting, active learning, labeling complexity.

I. Introduction

TWO most important factors for building a reliable visual object detection system are gathering enough representative training data and having an efficient learning method. Labeling sufficient data for training a reliable object detector is costly. Moreover, obtaining good samples for learning is not an easy task. There have been many attempts to use unlabeled data for training a classifier in semi-supervised learning fashion. The underlying idea of this approach is to train a classifier on partially (usually small set of) labeled samples and exploit the unlabeled data to improve the classifier and meanwhile predict labels for the unlabeled samples. The task can be done in a co-training, self-training, or conservative learning framework [10], [17], [19], [22]. One crucial issue of these approaches is, the proposed systems may suffer from the uncertainty in predicting label of the unlabeled samples. This mistake in prediction would be danger to the system [17], [19], [8].

Boosting methods have been widely used for solving many computer vision problems with impressive results [7], [23], [24], [14], [21], [22]. The spirit of boosting is a powerful ensemble learning algorithm, which combines a number of weak learners to produce a final strong classifier at high accurate. Adaboost learning algorithms are currently one of the fastest and most accurate approaches for object classification. Recently, there has been a considerable interest in using online boosting for learning an object detection system. Initiated by successful work proposed by Oza [15], a number of works with impressive result have been reported [8], [5], [19], [16]. Online boosting based approach has been proposed to effectively train a detector and avoids labeling data in advance. In a pure online boosting setting for object detection, there is no need to label data before learning, and there is no need to train an initial classifier in prior. Samples are sequentially labeled and presented to the system, the classifier is updated and the sample can be discarded. One would expect not to make serious mistake in labeling samples (since we have a human operator). The classifier is available at any time of the learning process. The learning approach is efficient and flexible. Besides, there have been also number of successful works in using active learning for training a visual object detection system [20], [1], [25], [6].

However, up to our knowledge, there has been no reported work in combining active learning and online boosting technique for further reducing hand-labeling effort, meanwhile obtaining fast and efficient training of the detector. And, there is no attempt to exploit the observed samples during training to obtain a stable classifier over the whole training process. Our approach will tackle the above issues in a systematic way. Firstly, we propose a strategy to integrate bootstrap training and self-learning in a single framework, which allows to reduce hand labeling effort meanwhile increasingly improve classifier. The strategy is done by exploiting the availability of the classifier during learning to generate good samples for learning and do self-updating the classifier. Besides, the update procedure in self-training ensures a balance of data, which is one important factor in training a classification system. Secondly, we employ a re-updating strategy to overcome the issue of "drifting" of classifier due to over adaptive to changing of object and background. This is done by allowing the classifier to re-update on seen data whenever it makes mistake on learned samples. We implement our framework as a wrapper around the training process of online boosting procedure, which act as a sub-algorithm working in semi-automatic self-training fashion. The applications target any visual object learning/detection problem that can be formulated for sequence learning, where the data arrives as streamline [1], [3], [11], [12], [13] and the human operator is able to rapidly present new object models to the system and provide feedback on the most informative and hard to classify samples. After training of the system, beside the main result of a desired classifier, training data set is also obtained.

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Our paper is organized as the following. Section 2 gives description of our approach. Section 3 is dedicated to experiments and results. Finally, section 4 is for discussion and future work.

II. Description of the system

In this section, we briefly introduce the online boosting algorithm which we based on to build our system. We then present our algorithm with the bootstrap procedure, the self-training strategy and the verification process. Theoretical justification and some discussion are presented after that.

A. The online boosting based detector

In principle, any online learning algorithm for object detection can be used as sub-algorithm in our framework. In this work, we focus on exploiting the online learning algorithm proposed by Grabner and Bischof [5]. In [5] an online boosting classifier has been designed to select features to discriminate the object from background. On-line boosting for feature selection is based on introducing "selectors" and performing on-line boosting on these selectors. Each selector $h^{sel}(\mathbf{x})$ holds a set of M weak classifiers $\{h_1^{weak}(\mathbf{x}), \ldots, h_M^{weak}(\mathbf{x})\}$ and selects one of them

$$h^{sel}(\mathbf{x}) = h_m^{weak}(\mathbf{x}) \tag{1}$$

according to an optimization criterion (the estimated error e_i of each weak classifier h_i^{weak} such that $m = \arg\min_i e_i$). Training a selector means that each weak classifier is updated and the one with the lowest estimated error is selected. Similar to the off-line case, the weak classifiers correspond to features, i.e. the hypotheses generated by the weak classifier are based on the response of the features.

The detector is trained using a novel on-line version of Adaboost. The algorithm performs on-line updating on the ensembles of features during the training process. In particular, the on-line training of AdaBoost for feature selection works as follows: First, a fixed set of N selectors, $h_1^{sel}, .., h_N^{sel}$, is initialized randomly with weak classifiers, i.e. features. When a new training sample $\langle \mathbf{x}, y \rangle$ arrives, the selectors are updated. This update is done with respect to the importance weight λ of the current sample. For updating the weak classifiers, any on-line learning algorithm can be used. The weak classifier with the smallest estimated error is chosen by the selector. The corresponding voting weight α_n and the importance weight λ of the sample are updated and passed to the next selector h_{n+1}^{sel}. The weight increases if the example is misclassified by the current selector and decreases otherwise. Finally, a strong classifier is obtained by linear combination of N selectors.

$$h^{strong}(\mathbf{x}) = \operatorname{sign}\Big(\sum_{n=1}^{N} \alpha_n \cdot h_n^{sel}(\mathbf{x})\Big) \tag{2}$$

In contrast to the off-line version a classifier is available at any time and can be directly evaluated which allows to provide immediate user feedback at any stage of the training process.

The training approach has been shown to be an efficient learning framework with fast and flexible training a detector. This is done without having to label training data in advance [18], [13]. By on-line interactive training, the classifier is updated as a new sample is provided, therefore we can reduce effort for labeling of training samples. For more details, see [5], [13].

B. The learning algorithm

In a purely on-line learning version, the training process is performed by iteratively labeling samples from the images and updating parameters for the model. The labeled samples can be positive or negative. An active learning strategy is applied. The idea is that the user has to label only examples which are not correctly classified by the current classifier. The classifier is evaluated and updated after each labeling of a sample. By interactive training, one can intuitively choose to label the most informative and discriminative sample at each update, which allows the parameters of the model to be updated in a greedy manner with respect to minimizing the detection error. It also avoids labeling redundant samples that do not contribute to the current decision boundary. Therefore this saves a lot of labeling effort.

Algorithm 1 Active learning process

1: Initialize parameters for the classifier as in [5]
2: **while** there exists an undetected object on current image **do**
3: Label one positive sample
4: Update parameters for the classifier with the labeled sample
5: **end while**
6: **while** non-stop-criteria **do**
7: Evaluate the current classifier on current image
8: Determine false positives on current image
9: Use false positives as negative samples to update classifier
10: Perform step 2-4 on new image for missed detections
11: Re-update the classifier on seen samples, if necessary
12: **end while**

In our framework, we make further steps to greatly reduce manual labeling effort for training. Our learning framework is implemented as a wrapper around the online boosting-based learning version. The learning process is shown in *Algorithm 1*. During the training process, we need only to label few positive samples. Negative samples are automatically generated using the availability of the classifier at each update iteration. After short time training at the beginning, the classifier is significantly improved, only weakly or missed detections are labeled as positive samples, only false positives are used as negatives to update the classifier. Updates really focus on hard samples. This strategy greatly reduce label complexity and allows fast training. In a detail description:

- Step 2-4 implement one-class classification learning procedure. In which the classifier is able to learn to discriminate object from background solely on the basis of

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positive samples. This procedure is performed whenever a new training image arrives, and there is no need to perform update if all objects in current image have been well detected.

- The bootstrap procedure is performed at step 7-8. At each update of the classifier, the current updated classifier is evaluated on current image. This results in a number of detections, which include detected (true) object(s), and usually false positives. These false positives are patches from background and are actually hard samples to learn (samples that lie near decision boundary). So, naturally we use these false positives as negatives samples for updating the classifier (bootstrapping). Therefore, there is no need to label negative samples for training.
- Our active learning strategy is performed at step 9-10. After a few clicks for positive updates, the classifier is significantly improved. By evaluating the current classifier on training image, detections are obtained. These detections (on training data) can be used as positive samples to update the classifier, so that the user does not have to label such samples. The human supervisor can decide whether to update the classifier on these true positive samples or not. This is usually not necessary for samples which are well detected (detections with high confidence). We thus force the classifier to update only on hard samples, i.e. weak detection (detected with low confidence) or missed detections of either positive or negative classes, with respect to the decision boundary of the current classifier. Therefore fewer update and less hand labeling effort can be achieved. For the balancing of training data, an alternative updates on newly generated positive and negative samples can be used. Thus, asymmetric problem is handled naturally by our updating mechanism, without needing a complicated procedure for tuning parameter of the classifier as in [16]. In summary, the training classifier is exploited to automatically generates good samples for learning and incrementally improve itself by update on newly obtained samples. A smooth decision boundary can be obtain since it is refined after updates on really hard samples.
- The verification process: because the classifier is adaptive to newly coming samples, it may make wrong decision on some sample that it has learned. The over-adaptiveness makes the classifier unstable. To overcome this, we employ a re-updating strategy on observed samples. This is done by storing labeled samples and regularly reapplying the training classifier to monitor if there is any missed classification so far. If there exists a missed classification on this, the classifier is updated. In the spirit of boosting, the re-update for missed detections can be interpreted as more attention has to pay on hards samples, or to give more weight on samples that difficult to classify. By storing parameters of the current training classifier and seen data, we can retrain it and make use of pretrained classifier any time, if necessary. This results in more accurate and stable classifier.

After training, the detection is performed by applying the trained classifier exhaustively on the images. An object region is considered to be detected if the output confidence value of the classifier is above a threshold, i.e. zero. This can be done very fast since we use efficient representation of data and simple architecture of the classifier.

C. *Theoretical justification*

By normalizing the boosting weight $\alpha = \frac{\sum_{n=1}^{N} \alpha_n \cdot h_n(\mathbf{X})}{\sum_{n=1}^{N} \alpha_n}$, it can be interpreted as a confidence measure for the prediction of a sample. Since we are learning a discriminative model, we set our goal to minimize the classification error instead of maximizing the model likelihood. Therefore, instead of learning a full data set, we learn only a small set of data, which is a set of samples that are close to the estimated decision boundary.

It has been shown in the literature that active learning approaches reduce labeling complexity, achieves high accuracy over random sampling, and reduce generalization error [20], [11], [12]. In our framework, we perform effective sampling by labeling samples at the estimated decision boundary instead of the unknown boundary. It is more likely that the algorithm will make error on samples that close to its current decision boundary. We make a further step for greedy improvement of a detector trained by active learning. Update is performed only on missed detection, which can be either positive or negative, which are samples that lie near the decision boundary and hard to classify. By this update strategy, the algorithm monotonically deceases its true error rate with each mistake and the error rate deceases exponentially with the number of mistakes [12]. Thus, our labeling strategy and updating mechanism greedily reduces error meanwhile progressively improving the classifier.

III. Experiment and Result

We conducted experiments on challenging data sets for a number of specific object detection problems. The main goal is to show the efficiency of learning a visual object detector by our proposed method compared to the conventional online boosting learning. The first experiment is performed for a hand detection problem, which is a problem having important applications in sign language and human machine interactions[9], [4]. This typical visual learning problem is well suited our approach. The second experiment is for the problem of detection of cars from a large scale aerial images. This is a challenging object detection problem where the online boosting algorithm has been shown to be an efficient approach [13].

A. *Data sets*

For the first experiment, we recorded two video sequences of hand movements. In which hand postures appear with vast changes of articulated and deformed hand object in a complex background. Some appearances of hands are shown in Fig. 1.

One sequence is use for training and the other one is for testing. The training sequence has a length of 1384 frames, the test sequence has 1976 frames. Each frame contain a hand

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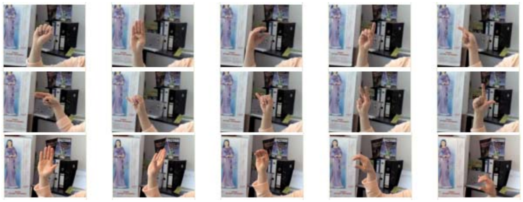


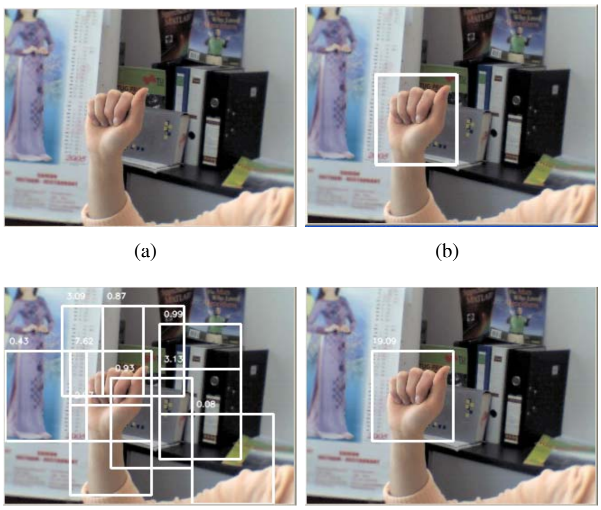
Fig. 1. Examples of hand appearances.

Fig. 2. Examples of car appearances.

appearance with different posture. For the second experiment, we used the Graz data as in [13]. The data set includes two large scale aerial images, each image has a size of 4000x4000 pixels. One image is used for training and the other one is for testing. The test image contains 324 cars. To setup the experiment, we splitted these huge images into subimages with overlapping. Each subimage has a size of 500x500, and may not contain a car. Some appearances of cars are shown in Fig. 2. For detail about data set and system setting, see [13].

B. Interactive training process

We start with a random classifier which comprises of 250 weak classifiers and 200 selectors. The classifier is improved after providing the training samples by the human operator. Thus, we make use of the advantages of active learning. Depending on each data set, during training we have labeled different number of samples. In particular, the training process started by labeling one image patch that contains an object as a positive sample to the system. The classifier is updated on this labeled sample. It is then evaluated and the detections are displayed. At each iteration of update, we can always evaluate the current classifier on current loaded image frame. Based on the output of the classifier, update is further processed on missed detections, i.e., we use false positives as negatives to continue update the classifier. The update here is performed in the same manner as for regular update on new coming samples. Fig. 3 shows the training process on a typical training sample. As one can see, a hand object is detected as region with highest



(a) (b)

(c) (d)

Fig. 3. Learning process: Improvement of classifier performance - (a) original image, (b) one click to select hand sample for training, (c) result after training the classifier with only one positive sample, and (d) the output of the classifier after training with the positive sample and false positives as negative samples.

confidence. However, missed detections are also present. With a self-training process on missed detections, we get a hand region learned and detected. The process is continued for the next image and so on.

C. Performance evaluation and comparison

Our main goal here is to demonstrate the robustness of our proposed approach over the conventional online boosting learning algorithm. Thus, in the following we will present the efficiency of learning process by our approach compare to the pure online boosting learning, and the performance of our system. For each experiment, we perform training two classifiers on training data with two training approaches. One classifier is trained by pure online boosting mechanism and the other is trained by our proposed strategy, on the same data set. We kept the same parameter setting for the classifier for each experiment. For the hand detection problem: to train the classifier by our proposed active boosting based learning, during training process we have manually labeled 32 positive samples and the system generated 42 negative samples for self-training; for the classifier trained by pure online boosting method, we have manually labeled all 70 positive and 80 negative samples.

For the car detection problem: to train the classifier by our approach, we have manually labeled 150 positive samples and the system generated 850 negative samples for self-learning; for the classifier trained by pure online boosting method, as reported in [13], the system needed 410 positive samples and 1010 negative samples. As one can see, our proposed learning method needs quite small amount of hand labeling samples for training in comparison to the pure online learning setting. Moreover, with the greedy strategy of with our approach, the system can learn quite fast. Some detection results for the hand detection problems are shown in Fig. 4. Yellow boxes shown detected hand regions. Some detection results for the

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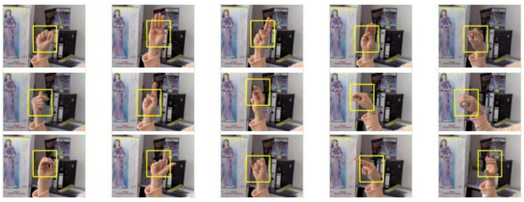


Fig. 4. Detections of hand appearances.

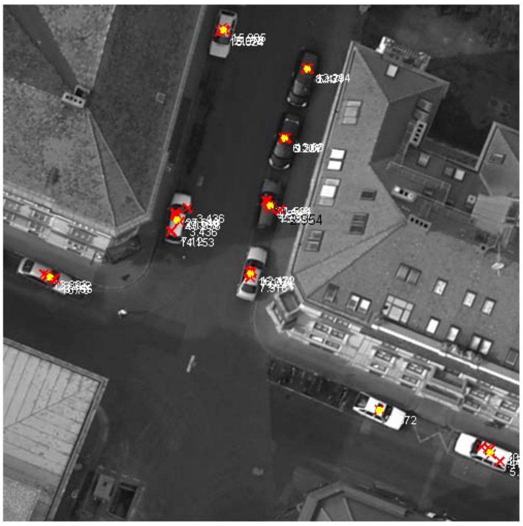
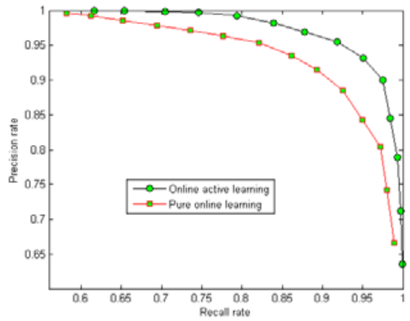
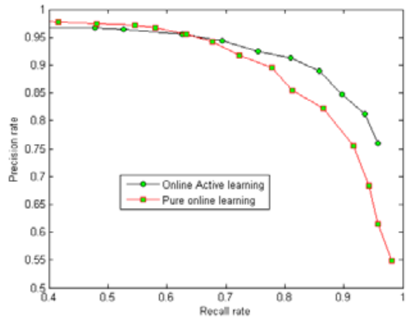


Fig. 5. Detections of cars.



(a)



(b)

Fig. 6. RPC of the system on (a) Hand detection problem and (b) Car detection problem.

car detection are shown Fig. 5. Yellow stars markers show the detections of cars after applying mean shift for post processing on red-cross markers. As one can see from the figures, all appearances of hands and car are have been detected correctly.

For a quantitative evaluation of performance of our approach, we report the results for the two experiment in term of recall-precision curves (RPC), which is a common measure for object detection [2]:

$$PR = \frac{\#TP}{\#TP + \#FP} \quad (3)$$

$$RR = \frac{\#TP}{\#TP + \#FN} \quad (4)$$

(*TP* - true positives, *FP* - false positives, *FN* - false negatives)

The recall rate (*RR*) shows us how many of the total positives we are able to identify. The precision rate (*PR*) shows how accurate we are at predicting the positive class. The RPCs characterizing the performance of our framework for the two experiments are given in Figure 6.

As one can see, the RPC curves of the systems learned by our approach (the upper ones) have some performance gain over the system trained by traditional online boosting approach. This is significant gain over the whole system since with the proposed approach we used much less hand labeling effort to provide samples to the system for learning. This greatly reduces label complexity to train a reliable object detection system.

IV. Conclusion

In this paper we have presented a new active learning framework for object detection based on an online boosting algorithm. The framework is implemented as a wrapper around the online boosting-based learning procedure. We have proposed to exploit the availability of the online learning classifier for automatically generating samples for training meanwhile increasingly improve performance. The seen data has been employed for verifying the classifier, which resulted in a more stable detector. We have demonstrated that by a simple modification of pure online boosting learning, an online boosting approach trained in this manner can achieve results comparable or even outperform a framework trained in conventional manner using much more labeling effort. Empirical experiments shown the effectiveness of our approach over pure online boosting setting in term of learning speed, accuracy, and stability. For future work, we will study the generalization ability of the proposed learning method for more complex object detection problem. The real-time performance of the system motivate us to apply the framework for some real-time application, such as object recognition.

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