Transductive Transfer Learning to Specialize a Generic Classifier Towards a Specific Scene

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Abstract: In this paper, we tackle the problem of domain adaptation to perform object-classification and detection tasks in video surveillance starting by a generic trained detector. Precisely, we put forward a new transductive transfer learning framework based on a sequential Monte Carlo filter to specialize a generic classifier towards a specific scene. The proposed algorithm approximates iteratively the target distribution as a set of samples (selected from both source and target domains) which feed the learning step of a specialized classifier. The output classifier is applied to pedestrian detection into a traffic scene. We have demonstrated by many experiments, on the CUHK Square Dataset and the MIT Traffic Dataset, that the performance of the specialized classifier outperforms the generic classifier and that the suggested algorithm presents encouraging results.

1 INTRODUCTION

In the last fifteen years, we have seen many generic object detectors which perform detection in static images; we cite mainly the Viola-Jones detector (Viola and Jones, 2001) and the HOG-SVM Detector proposed by Dalal and Triggs (Dalal and Triggs, 2005). However, object detection and classification on a specific video surveillance scene are still two interesting and challenging tasks in computer vision because the algorithm needs to find objects in spite of their scale and position in the video's frame, as well as other variation factors like illumination and occlusions. In addition, a generic training dataset contains all possible appearances of the object in different views and a significant number of negative images that can not be useful for a specific scene, which has a unique static background and contains objects with only a few views. This diversity of object views and/or of background class leads to weak performances of a generic detector in a particular scene.

As a solution to these problems, Transfer Learning (TL) approaches (also referred to as cross-domain adaptation approaches) have shown interesting results by using knowledge from the source domains to learn a classifier/detector for the target domain containing unlabelled data or only a few labelled samples. Pan and Yang (Pan and Yang, 2010) conducted a survey, providing valuable references for interested readers. Their work gave the main differences between the static learning system and the transfer learning one. Also, they presented the TL works in three types: inductive, transductive and unsupervised. The inductive type supposes the presence of some labelled samples in the target domain. Whereas, the transductive type deals with a target domain without any labelled data and assumes that the distribution of the source domain is different from the target one, though they are actually related. The unsupervised type handles unlabelled data into both source and target domains. The two first types are more presented in the literature. The transductive TL type allows avoiding data labelling in each scene and offers improving object detection/classification in different videos. These were the reasons that motivate us to suggest an original formalization of transductive transfer learning based on a sequential Monte Carlo filter (Doucet et al., 2001) in order to specialize a generic classifier to a target domain.

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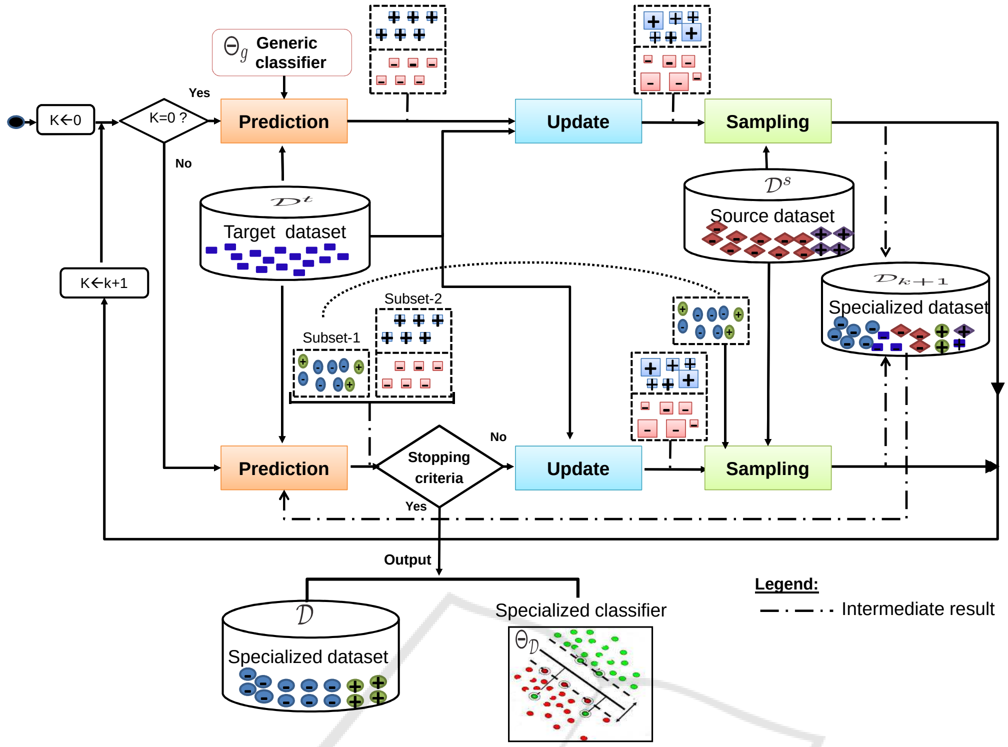


Figure 1: A synthetic block diagram of the proposed approach. The unknown target distribution is approximated through a sequential Monte-Carlo algorithm.

This filter selects training dataset samples that are considered to be realizations of the joint probability distribution between features' samples and object classes corresponding to the target scene.

Figure 1 shows the block diagram of our approach which aims to estimate the hidden distribution of the target dataset through a set of iterations. At the first iteration, a generic classifier is used to predict a set of samples from the target dataset. Then, the update step determines the relevance of each samples by using an observation function. After that, the sampling step proposes the first specialized dataset from target and source samples. The observation function utilizes widely information which is extracted from the target scene. This is close to Wang's (Wang et al., 2012a) visual cues and those used by Chesnais (Chesnais et al., 2012).

The process is the same at a different iteration, but the prediction step uses a specialized classifier, trained on a dataset built at the previous iteration, to propose new samples belonging to the target dataset. The sampling step draws a new training dataset from: 1) the previous specialized dataset, 2) the target dataset and 3) a source dataset to approximate the target distribution.

In this paper, our main contributions are:

- Proposing an original formalization of transfer learning for the specialization of a generic classifier to a target domain;
- Applying our algorithm to detect pedestrians in traffic video sequences;
- Evaluating our proposed method to the state of the art on two public datasets.

The next section gives some related works. Section 3 describes the proposed approach. Section 4 presents a pedestrian detection framework as an application of the method to validate our concepts. Our experiments and results are provided in section 5. The last section is a conclusion and gives some perspectives.

2 RELATED WORKS

In this section we describe three categories of transfer learning works which provide specific detectors/classifiers to a particular domain. Then, we are limited to the closest group that suggests to improve pedestrian detection into a video surveillance scene, corresponding to the application we present to validate our specialization framework.

The first category of TL methods has aimed to modify the parameters of a source learning model to improve its functioning in a target domain, as presented in (Aytar and Zisserman, 2011; Tommasi et al., 2010; Pang et al., 2011; Dai et al., 2007; Yang et al., 2007), by leveraging the visual knowledge of source data or other forms of prior knowledge. Wang *et al.*(Wang et al., 2012b) proposed to leverage a vocabulary tree as a binary vector to encode visual example for detector adaptation. In addition, Salakhutdinov *et al.* (Salakhutdinov et al., 2010) used a higher-order knowledge abstracted from previously learned classes to predict the label of a new class by using only one sample.

The second category of works has dealt with distribution adaptation to reduce the difference between source and target domains. For instance, Pan *et al.* (Pan et al., 2011) learnt a low-dimensional space where the distance in marginal distributions could be reduced. Moreover, Quanz *et al.* (Quanz et al., 2012) minimized both marginal and conditional distributions. In contrast to these two methods, which expect either the presence of multi- source domains or labelled target data, Long *et al.* (Long et al., 2013) suggested a new approach able to jointly adapt the marginal and conditional distributions using a procedure to reduce the dimension of data in both domains and build a new feature representation that would fill in the distributions' difference.

The third category of transfer learning methods has automatically selected training samples that have given a better model for the target task. Lim *et al.* (Lim et al., 2011) put forward a transfer learning approach based on borrowing training samples from similar categories to the target class. Then, they applied a set of transformations to the borrowed samples to generate the target dataset. Inspired from this, Tang *et al.* (Tang et al., 2012) used a binary-valued variables to weight examples, which would be added or excluded from the training set.

In this part, we have focussed on some works related to pedestrian detection application. This group is based on using or building an automatic labeller to collect data from the target domain. Rosenberg *et al.* (Rosenberg et al., 2005) utilized the decision function of an object appearance classifier to select the training samples from one iteration to another. Levin *et al.* (Levin et al., 2003) used a system with two independent classifiers to collect unlabelled data. The labelled data with high confidence, by one classifier or another, were added to the training data to retrain the two classifiers. Another way to automatically collect new samples is to use an external entity called "oracle". An oracle may be built using a single algorithm or combine and/or merge multiple algorithms. In (Nair and Clark, 2004), an algorithm based on background subtraction was presented. Also, Chesnais *et al.* (Chesnais et al., 2012) proposed an oracle composed of three independent classifiers (appearance, background extraction, and optical flow). Furthermore, some solutions concatenate the source dataset with new samples, which increases the size of the dataset during iterations. Others are limited only to the use of new samples, which results in losing pertinent information of source samples. Another solution was proposed in (Wang et al., 2012a; Tang et al., 2012; Zeng et al., 2014; Wang and Wang, 2011; Wang et al., 2014; Wang et al., 2012b). It collected new samples from the target domain and selected only the useful ones from the source dataset. Wang *et al.* (Wang et al., 2014) used many contextual cues such as pedestrian motion, road model (pedestrians, cars ...), location, size and objects' visual appearances to select positive and negative samples of the target domain. In fact, their method was based on a new SVM variant to select only source samples that were good for the classification in the target scene. Zeng *et al.* (Zeng et al., 2014) utilized Wang's approach (Wang et al., 2014) as an input to their deep model, which learnt the distribution of target domain and re-weighted samples from both domains.

Except Zeng *et al.* (Zeng et al., 2014), all the latter approaches did not learn or estimate the target domain distribution. However, our Transductive Transfer Learning framework based on a Sequential Monte Carlo (TTL-SMC) aims to approximate iteratively the joint probability distribution between the feature descriptors' samples and the object classes corresponding to the target scene. This is done by using the Sampling Importance Resampling (SIR) algorithm (Doucet et al., 2001) to select both target and source samples according to the output of an observation function and a visual similarity weighting procedure.

3 CLASSIFIER SPECIALIZATION BY A SEQUENTIAL MONTE CARLO FILTER

This section describes the core of the proposed specialization method done by a transfer learning approach based on a sequential Monte Carlo filter.

3.1 Context

Let us have a source dataset, a generic detector – which can be learnt from this source dataset – and a video sequence of a target scene. A specialized classifier and an associated specialized dataset are to be generated. A huge number of unlabelled samples can be generated from the target video.

We assume that the unknown jointed distribution between the target features and the associated class labels can be approximated by a set of well chosen samples. This latter can be used as a specialized training dataset. We propose to approximate this distribution by a sequential Monte Carlo filter.

Let $\mathcal{D}_k \doteq \{\mathbf{X}_k^{(n)}\}_{n=1,..,N}$ be a specialized dataset of size N at an iteration k, where $\mathbf{X}_k^{(n)} \doteq (\mathbf{x}^{(n)}, y)$ is the sample number n, with $\mathbf{x}$ being its feature vector, and y is its label, with $y \in \mathcal{Y}$. Basically, in a detection case, $\mathcal{Y} = \{-1; 1\}$, where 1 represents the object and -1 represents the background (or non-object class). In addition, $\Theta_{\mathcal{D}_k}$ is a specialized classifier at an iteration k, which is trained on the specialized dataset built at the previous iteration $(k-1)$. A classifier assigns a label y to a feature vector $\mathbf{x}$. We have used a generic classifier Θ_g at the first iteration.

A source dataset $\mathcal{D}^s \doteq \{\mathbf{X}^{s(n)}\}_{n=1,..,N^s}$ of N^s labelled samples is defined. Moreover, a large target dataset $\mathcal{D}^t \doteq \{\mathbf{x}^{t(n)}\}_{n=1,..,N^t}$ is available. This dataset is composed of N^t unlabelled samples provided by a multi-scale sliding window extraction strategy on the target video sequence.

3.2 Sequential Monte Carlo Filter

The suggested transfer learning algorithm is based on the assumption that the target distribution can be approximated by the samples of the specialized dataset. These samples are initially unknown but they can be estimated using an observation process and some prior information from the target scene.

We define $\mathbf{X}_k$ a hidden state associated to an unknown sample at an iteration k and $\mathbf{Z}_k$ an observation extracted from the target video sequence. Based on our assumption, the target distribution can be approximated by iteratively applying equation (1):

$$p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k+1}) = C.p(\mathbf{Z}_{k+1}|\mathbf{X}_{k+1}) \int_{\mathbf{X}_k} p(\mathbf{X}_{k+1}|\mathbf{X}_k) p(\mathbf{X}_k|\mathbf{Z}_{0:k}) d\mathbf{X}_k \quad (1)$$

where $C = 1/p(\mathbf{Z}_{k+1}|\mathbf{Z}_{0:k+1})$.

The sequential Monte Carlo method approximates the posterior distribution $p(\mathbf{X}_k|\mathbf{Z}_k)$ by a set of N particles (samples in this case), according to equation (2):

$$p(\mathbf{X}_k|\mathbf{Z}_k) \approx \frac{1}{N} \sum_{n=1}^{N} \delta(\mathbf{X}_k^{(n)}) \approx \{\mathbf{X}_k^{(n)}\}_{n=1,..,N} \quad (2)$$

Therefore, a sequential Monte Carlo filter is used to estimate the unknown jointed distribution between the features of the target samples and the associated class labels. We suppose that the recursion process selects relevant samples for the specialized dataset from one iteration to another, which leads to converge to the right target distribution and which makes the resulting classifiers more and more efficient.

The resolution of equation (1) is done in three steps: prediction, update and sampling. These steps are the same as those into the particle filter used, in general, to solve tracking problems in computer vision (Isard and Blake, 1998; Smal et al., 2007; Mei and Ling, 2011). An illustration of our proposed algorithm is shown in Figure 1 and the details of the three main steps are described in the following subsections.

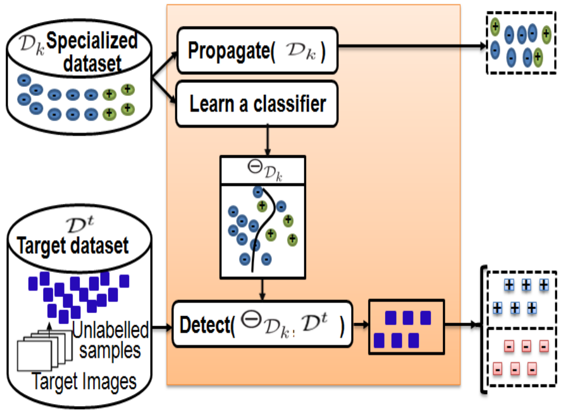


Figure 2: Details of the prediction step processing.

3.2.1 Prediction Step

Figure 2 shows an overview of the prediction step processing at a given iteration. This step consists in applying the Chapman-Kolmogorov equation (3):

$$p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k}) = \int_{\mathbf{X}_k} p(\mathbf{X}_{k+1}|\mathbf{X}_k) p(\mathbf{X}_k|\mathbf{Z}_{0:k}) d\mathbf{X}_k \quad (3)$$

It uses the term $p(\mathbf{X}_{k+1}|\mathbf{X}_k)$ of the system dynamics between two iterations to propose a specialized dataset $\mathcal{D}_k \doteq \{\mathbf{X}_k^{(n)}\}_{n=1,..,N^s}$ producing the approximation (4):

$$p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k}) \approx \{\tilde{\mathbf{X}}_{k+1}^{(n)}\}_{n=1,..,\tilde{N}_{k+1}} \quad (4)$$

We note $\tilde{\mathcal{D}}_{k+1}$ the specialized dataset predicted for an iteration $(k+1)$ where $\tilde{\mathbf{X}}^{(n)}_{k+1}$ is the predicted sample n and $\tilde{N}_{k+1}$ is the number of samples provided by the prediction step. In our case, this predicted dataset is composed of two subsets:

1. Subset 1: It corresponds to sub-sampling the previous specialized dataset to propagate the distribution. The ratio between the positive and negative classes (typically the same as the source dataset) should be respected. This subset approximates the term $p(\mathbf{X}_k|\mathbf{Z}_{0:k})$ in equation (1), according to equation (5):

$$p(\mathbf{X}_k|\mathbf{Z}_{0:k}) \approx \{\mathbf{X}^{*(n)}_{k+1}\}_{n=1,..,N^*} \quad (5)$$

   where $\mathbf{X}^{*(n)}_{k+1}$ is the sample n selected from $\mathcal{D}_k$ to be in the dataset of the next iteration $(k+1)$ and N^* represents the number of samples in this subset with $N^* = \alpha_t N^s$, where $\alpha_t \in [0,1]$. The parameter α_t determines the number of samples to be propagated from the previous dataset.

2. Subset 2: It is a part of target samples selected as " positive " by a classifier trained on D_k and applied on the target dataset D^t. This subset contains several samples which are not really positive, in particular at the first iteration where we use a generic classifier that gives a weak result.

   At this step, all samples returned by (6) are supposed to be both positive and negative and the decision between the two labels will be provided by the observation function in the update step.

$$\{\breve{\mathbf{X}}^{(n)}_{k+1}\}_{n=1,..,\breve{N}_k} \doteq \{(\mathbf{x}^{(n)}, y)\}_{y\in\mathcal{Y}\ ;\mathbf{x}^{(n)}\in\mathcal{D}^t / \Theta_{\mathcal{D}_k}(\mathbf{x}^{(n)})>0} \quad (6)$$

   $\breve{\mathbf{X}}^{(n)}_{k+1}$ is the n^{th} target sample proposed to be included in the dataset of the next iteration $(k+1)$. Initially, this subset has been classified positive by $\Theta_{\mathcal{D}_k}$.

In what follows, we note the functions returning these two subsets by $Propagate(\mathcal{D}_k)$ and $Detect(\Theta_{\mathcal{D}_k}, \mathcal{D}^t)$, respectively.

3.2.2 Update Step

The update step assigns a weight $\breve{\pi}^{(n)}_{k+1}$ to each sample $\breve{\mathbf{X}}^{(n)}_{k+1}$ returned by the function $Detect(\Theta_{\mathcal{D}_k}, \mathcal{D}^t)$ to define the likelihood term (7) by using an observation function.

$$p\left(\mathbf{Z}_{k+1}|\mathbf{X}_{k+1} = \breve{\mathbf{X}}^{(n)}_{k+1}\right) \propto \breve{\pi}^{(n)}_{k+1} \quad (7)$$

The observation function uses visual contextual cues and prior information extracted from the target video sequence like object motion, background subtraction and/or object path model, which are used extensively in the state of the art. The output of this step is a set of weighted target samples, which will be referred to as "the weighted target dataset" hereafter (8):

$$\{(\breve{\mathbf{X}}^{(n)}_{k+1}, \breve{\pi}^{(n)}_{k+1})\}_{n=1,..,\breve{N}_{k+1}} \quad (8)$$

where $(\breve{\mathbf{X}}^{(n)}_{k+1}, \breve{\pi}^{(n)}_{k+1})$ represents a target sample and its associated weight and $\breve{N}_{k+1}$ is the number of samples that have a weight different from zero.

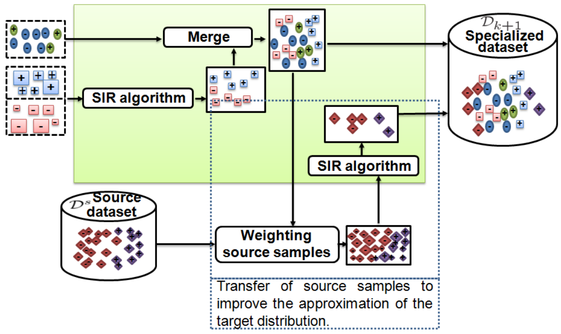


Figure 3: Details of the sampling step.

3.2.3 Sampling Step

The sampling step in our case determines exactly which samples would be included in the specialized dataset for the next iteration. Figure 3 illustrates the details about this step. On the one hand, we use the SIR algorithm to generate a new set of unweighted target samples from the weighted target dataset provided by the update step. This last weighted target dataset approximates the conditional distribution $p(\breve{\mathbf{X}}_{k+1}|\mathbf{Z}_{k+1})$ of the target samples given by the observations. After applying the SIR, we have a set of target samples that approximate the same distribution (9):

$$p(\breve{\mathbf{X}}_{k+1}|\mathbf{Z}_{k+1}) \approx \{\breve{\mathbf{X}}^{*(n)}_{k+1}\}_{n=1,..,\breve{N}^*_{k+1}} \quad (9)$$

where $\breve{\mathbf{X}}^{*(n)}_{k+1}$ is the selected sample n for the next iteration $(k+1)$ from the weighted target dataset.

At this level, the posterior distribution $p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k+1})$ is approximated by (10):

$$p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k+1}) \approx \{\mathbf{X}^{*(n)}_{k+1}\}_{n=1,..,N^*} \cup \{\breve{\mathbf{X}}^{*(n)}_{k+1}\}_{n=1,..,\breve{N}^*_{k+1}} \quad (10)$$

On the other hand, we propose to utilize the source distribution to improve the estimation of the target one. The new specialized dataset is extended by transferring samples from the source dataset without changing the posterior distribution. The probability that each source sample belongs to the

Table 1: Functions and notations used in this paper.

Notation: definition
-$Detect(\Theta_{\mathcal{D}_k}, \mathcal{D}^t)$: applies a classifier $\Theta_{\mathcal{D}_k}$ on the target dataset $\mathcal{D}^t$ to predict a set of samples.
-$Propagate(\mathcal{D}_k)$: selects samples to propagate from $\mathcal{D}_k$ to $\mathcal{D}_{k+1}$.
- $Learn(\Theta, \mathcal{D})$: learns a classifier Θ on the dataset $\mathcal{D}$.
- Obs_fn: the observation function.
- $\mathbf{p}$: is a spatio-temporal Region Of Interest (ROI) position into the target video-sequence ($\mathcal{D}^t$).
- $compute\_overlap(\mathbf{p}, \mathcal{D}^t)$: computes an overlap_score of ROI $\mathbf{p}$.
- $compute\_accumulation(\mathbf{p}, \mathcal{D}^t)$: computes an accumulation_score of ROI $\mathbf{p}$

target distribution $p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k+1})$ is estimated from the current set of target samples by a non parametric method (KDE or KNN estimator). Based on these probabilities, we apply the SIR algorithm to select the source samples that approximate $p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k+1})$ according to equation (11) :

$$p(\mathbf{X}_{k+1}|\mathbf{Z}_{0:k+1}) \approx \{\mathbf{X}_{k+1}^{s*(n)}\}_{n=1,..,\check{N}_{k+1}^{s*}} \quad (11)$$

where $\mathbf{X}_{k+1}^{s*(n)}$ is the source sample n selected to be in the specialized dataset at the iteration $(k+1)$ and $\check{N}_{k+1}^{s*}$ is the number of the selected source samples. This number is determined using equation (12):

$$\check{N}_{k+1}^{s*} = N^s - (N^* + \check{N}_{k+1}^{*}) \quad (12)$$

Finally, the new dataset for the iteration $(k+1)$ is built by the union of three subsets (13):

$$\mathcal{D}_{k+1} \doteq \{\mathbf{X}_{k+1}^{*(n)}\}_{n=1,..,N^*} \cup \{\check{\mathbf{X}}_{k+1}^{*(n)}\}_{n=1,..,\check{N}_{k+1}^{*}} \cup \{\mathbf{X}_{k+1}^{s*(n)}\}_{n=1,..,\check{N}_{k+1}^{s*}} \quad (13)$$

The process stops when the ratio $(|\tilde{\mathcal{D}}_{k+1}|/|\tilde{\mathcal{D}}_k|)$ ($|\bullet|$ represents the dataset cardinality.) exceeds a previously determined threshold α_s.

Table 1 defines the functions and notations that are used in the rest of the paper, and Algorithm 1 describes the TTL SMC process.

4 APPLICATION TO PEDESTRIAN DETECTION

This section presents an application of our TTL-SMC framework to specialize a generic detector to a specific traffic scene which ameliorates pedestrian detection with an automatic labelling of target data.

In the following sub-sections, the three stages of the proposed algorithm are presented.

Algorithm 1: Transfer learning for specialization.

Input: Source dataset $\mathcal{D}^s$
Generic classifier Θ_g
Target video scene and the associated dataset $\mathcal{D}^t$
Number of source samples N^s.
The parameter α_t, α_s.
Output: The last specialized dataset $\mathcal{D}$
The last classifier $\Theta_{\mathcal{D}}$

$k \leftarrow 0$
$stop \leftarrow false$
while $stop \neq true$ **do**
  if $(k = 0)$ **then**
    /* Prediction step */
    $N^* \leftarrow 0$
    $\tilde{\mathcal{D}}_{k+1} \leftarrow Detect(\Theta_g, \mathcal{D}^t)$
    /* Update step */
    $\{(\check{\mathbf{X}}_{k+1}^{(n)}, \check{\pi}_{k+1}^{(n)})\}_{n=1,..,\check{N}_{k+1}} \leftarrow Obs\_fn$
    /* Sampling step */
    $\mathcal{D}_{k+1} \leftarrow \{\check{\mathbf{X}}_{k+1}^{*(n)}\}_{n=1,..,\check{N}_{k+1}^{*}} \cup \{\mathbf{X}_{k+1}^{s*(n)}\}_{n=1,..,\check{N}_{k+1}^{s*}}$
  else
    /* Prediction step */
    Learn $(\Theta_{\mathcal{D}_k}, \mathcal{D}_k)$
    $N^* \leftarrow \alpha_t N^s$
    $\tilde{\mathcal{D}}_{k+1} \leftarrow Propagate(\mathcal{D}_k) \cup Detect(\Theta_{\mathcal{D}_k}, \mathcal{D}^t)$
    if $(|\tilde{\mathcal{D}}_{k+1}|/|\tilde{\mathcal{D}}_k| >= \alpha_s)$ **then**
      $stop \leftarrow true$
      Break
    end if
    /* Update step */
    $\{(\check{\mathbf{X}}_{k+1}^{(n)}, \check{\pi}_{k+1}^{(n)})\}_{n=1,..,\check{N}_{k+1}} \leftarrow Obs\_fn$
    /* Sampling step */
    $\mathcal{D}_{k+1} \leftarrow$equation (13)
  end if
  $k \leftarrow k+1$
end while

4.1 Prediction Step

The prediction step consists in selecting randomly a set of samples (subset 1) from the specialized dataset of the previous iteration. In addition, a second set of detection proposals (subset 2) is provided by a detector trained on the previous specialized dataset and applied on the target video-sequence, using a multi-scale sliding windows strategy.

This strategy provides a set of samples that were classified by the classifier as pedestrian, but really there are both true and false detections (Figure 4). A spatial mean-shift is applied to merge the closest detections. Herein, we suppose that each detection of subset 2 can be either a positive sample or a negative one. Thus, each detection produces both a positive

Figure 4: Illustration of the prediction step result: Detections provided by a generic detector applied on frames of the CUHK_Square dataset.

sample and a negative one.

At the first iteration, it is to note that subset 1 is empty and that proposals composing subset 2 are given from a generic detector trained on the INRIA Person Dataset, in a similar way to the one proposed by Dalal and Triggs in (Dalal and Triggs, 2005).

In our application, we have trained the generic and the specialized classifiers using the SVMLight[1].

4.2 Update Step

This step computes a weight for each sample of "subset 2" using an observation function. This likelihood function is based on visual cues. We put forward two simple spatio-temporal cues: a background extraction overlap score and a temporal accumulation score.

We assume that pedestrians are moving and that a good detection occurs on a foreground blob. The overlap_score λ_o (14) compares the Region Of Interest (ROI) associated to one sample with the output of a binary foreground extraction algorithm.

$$\lambda_o \doteq \frac{2(ROI\_AREA \times FG\_AREA)}{ROI\_AREA + FG\_AREA} \quad (14)$$

where ROI_AREA is the area in pixels of the considered ROI and FG_AREA is the foreground area at the ROI position.

Additionally, false positive detections on background provide some ROIs that temporally "twinkle" on the target video-sequence. An accumulation_score λ_a is computed in order to detect such hard background regions, where the detector responds positively.

The observation function (Algorithm 2) assigns a high weight to a positive proposition if it has an overlap_score λ_o that exceeds a fixed threshold α_p, which is determined empirically. On the other hand, the accumulation_score gives information about negative propositions. A negative sample which has a big score λ_a can be a correct proposition;

[1] http://svmlight.joachims.org

Algorithm 2: Observation function.

Input: Subset-2 $\{\check{\mathbf{X}}_{k+1}^{(n)}\}_{n=1,..,\check{N}}$ with associated ROI position and size $\{\mathbf{p}_i\}_{i=1,..,\check{N}}$ into the target video-sequence
Target video sequence and associated dataset $\mathcal{D}^t$
α_p: overlap threshold
Output: Set $\{\pi_i\}_{i=1..,L}$ of weights associated to samples

for $i = 1$ to L **do**
  $\pi_i \leftarrow 0$
  `/* Visual contextual cues computation */`
  $\lambda_o \leftarrow compute\_overlap(\mathbf{p}_i, \mathcal{D}^t)$
  $\lambda_a \leftarrow compute\_accumulation(\mathbf{p}_i, \mathcal{D}^t)$
  `/* Weight assignment */`
  if $(\check{y}_i = pedestrian)$ **then**
    if $(\lambda_o \geqslant \alpha_p)$ **then**
      $\pi_i \leftarrow \lambda_o$
    end if
  else
    if $((\lambda_o = 0.0)\&(\lambda_a > 0.0))$ **then**
      $\pi_i \leftarrow \lambda_a$
    end if
  end if
end for

Figure 5: The observation function result at the iteration k: The assigned weight allows privileging one label from the two propositions. A green ellipse means the sample is correct according to the proposed label, a red rectangle means that the proposed label is not correct and a blue dotted rectangle means that the sample should be rejected.

i.e., it should have a high weight (an example of the observation function result is shown in Figure 5). Negative propositions are called "hard-examples" because they are classified by the previous detector as pedestrians, but currently they are not. The use of these samples in the next specialized dataset improves the performance of the specialized classifier. After applying algorithm 2, any proposition that has a null weight will be rejected.

4.3 Sampling Step

This step aims to select target and source samples in order to build a specialized dataset that approximates the target distribution.

The update step provides a weighted target dataset approximating the target distribution. A SIR algorithm is applied to build an unweighted target dataset which has the same number of samples as the weighted one.

The resulting dataset approximates the target distribution. In order to extend this dataset without altering the latter distribution, we propose to draw samples from the source dataset. The probability (weight) that each source sample belongs to the target distribution $\breve{\pi}_{k+1}^{s(n)}$ is computed using a non-parametric method based on the KNN algorithm (using the FLANN[2] library and an L2 distance on features). The SIR algorithm is used in order to select the source samples to be included in the specialized dataset. As the weights used in the SIR algorithm are proportional to the probability that a sample should derive from the target distribution, the resulting distribution is the same as the target one.

At the end of this step, three subsets are merged to produce the new specialized dataset: the propagated selection from the previous dataset, the unweighted target dataset and the new source dataset resulting from the SIR algorithm.

The specialization process stops when the ratio α_s is reached ($\alpha_s = 0.80$ fixed empirically in our case). Once the specialization is finished, the obtained detector can be used for pedestrian detection in the target scene based only on appearance.

5 EXPERIMENTS AND RESULTS

This section presents the experiments achieved in order to evaluate the specialization's performances. We have tested our method on two public traffic videos using the same setting as in (Wang and Wang, 2011; Wang et al., 2012a; Wang et al., 2014; Zeng et al., 2014).

- **The CUHK_Square Dataset (Wang et al., 2012a)**: It is a video sequence of road traffic which takes 60 minutes. We have used 352 images for the specialization, which have been extracted uniformly from the first half of the video. We have used for the test 100 images, which have been extracted from the second 30 minutes.
- **The MIT Traffic Dataset (Wang et al., 2009)**: It is a set of 20 short video sequences of a 90-minute video all in all. We have used 420 images for the specialization, which have been extracted uniformly from the 10 first videos. Also, 100 images are extracted from the second 10 videos for the test.

To evaluate the detection results of our specialized detectors on the CUHK_Square dataset and on the MIT Traffic dataset, we have used the ground truth provided by Wang *et al.* in (Wang et al., 2012a) and (Wang and Wang, 2011), respectively. The PASCAL rule (Everingham et al., 2010) is applied to calculate the rate of the true positives. A detection is considered good if the overlap area between the detection window and the ground truth exceeds 0.5 of the union area. The detection performances are compared using the Receiver Operating Characteristic (ROC) curve, presenting the pedestrian detection rate for a given false positive rate per image.

In the following sub-sections, the indication of a detection's rate is always related to one False Positive Per Image (FPPI=1). We first discuss the convergence of the specialization algorithm and the influence of the number of propagated samples (the parameter α_t) on the detection performances. Then, we compare the proposed algorithm with the state of the art methods on two public datasets.

5.1 Convergence of Specialized Detector

Figures 6 (a) and (b) compare the performance of the specialized detector at several iterations to the performance of the generic detector, on the CUHK_Square dataset and the MIT Traffic dataset, respectively. They show that the specialized detector trained by our TTL-SMC generates an increase in the detection rate from the first iteration. On the CUHK_Square dataset, the specialized detector performance exceeds that of the generic one by more than 30% and the curves show that the specialization converges after four iterations with a rate of true positives higher than 70%. On the MIT Traffic dataset, our framework improves the detection rate from 10% to 20% and it starts converging from the fourth iteration with 40% of true detections. The experiments demonstrate that the performance has improved weakly for the next five iterations (for clarity reasons, we have limited the visualization of the ROC at the tenth iteration) taking into account the average duration needed for selecting samples and training the specialized detector. Table 2 reports the average duration of a specialization's iteration on a machine Intel(R) Core(TM) i7- 3630QM 2.4G CPU

[2] http://www.cs.ubc.ca/research/flann/

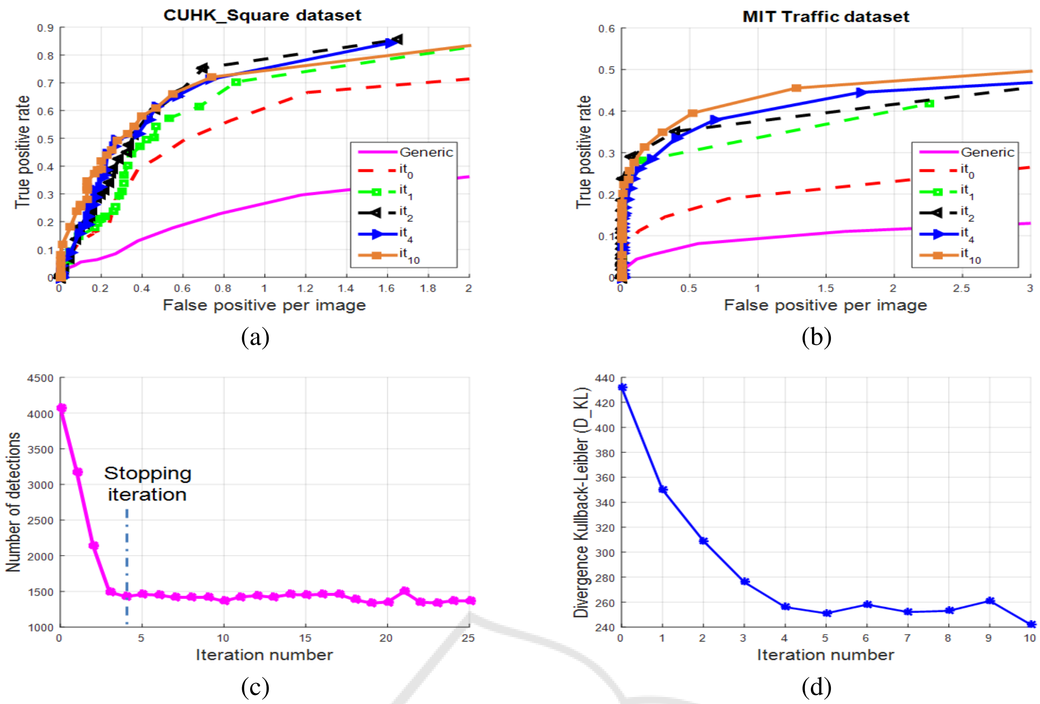


Figure 6: Convergence evaluation: (a) & (b) Comparison between the generic detector and the specialized detectors through several iterations, on the CUHK_Square dataset and the MIT traffic dataset, respectively. (c) Number of detections during iterations; it converges after the fourth iteration. (d) Divergence Kullback-Leibler between the positive samples of the specialized datasets for the first ten iterations and the true manually labelled positive samples of the specialization images.

to apply the detection and the observation function on each dataset with the designed number and size of images.

Table 2: Average duration of a specialization's iteration on the two datasets.

Dataset	Nb. images	Image size	Duration
CUHK	352	1440×1152	1 hour
MIT	420	4320×2880	3.5 hours

In addition to these latter considerations, we have noticed that the number of detections stabilizes from iteration 4, which corresponds to the stop iteration according to the stopping criterion α_s, defined previously (Figure 6-(c)).

In order to measure whether the estimated distribution converges toward the true target distribution, we have manually cropped samples to build a target labelled dataset. The Kullback-Leibler Divergence (KLD) has been computed between the specialized dataset, produced at each iteration, and the ground truth target dataset. Figure 6-(d) shows that the KLD decreases until having a minimal variation starting from iteration 4 (corresponding to the stopping iteration) on the CUHK_Square dataset. The recorded decrease in the KLD explains the convergence of the specialization process to the true target distribution.

5.2 Influence of Parameter α_t

The parameter α_t is used to adjust the number of samples that propagate from one iteration to another.

Table 3 shows the performances of detectors with different values of α_t. It presents a maximal detection rate, which is equal to 77%, corresponding to the value of 0.75.

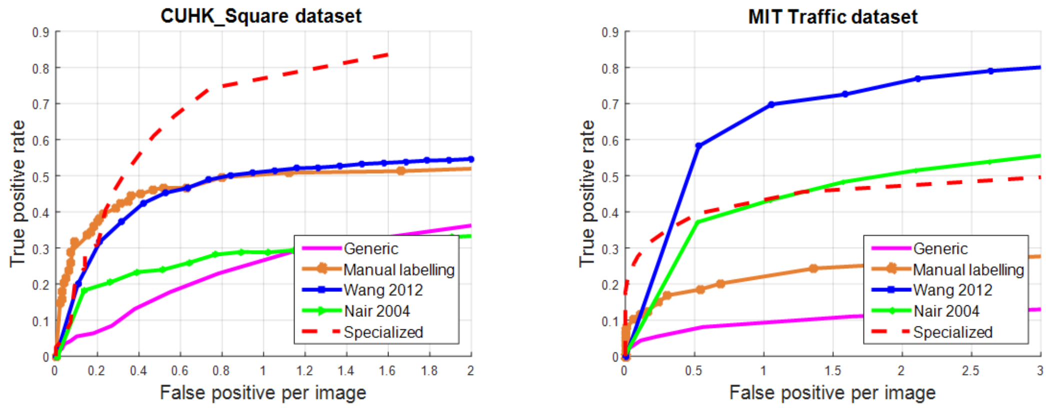
Table 3: Detection rate of different detectors for various values of parameter α_t relative to FPPI=1.

α_t	**0.1**	**0.25**	**0.5**	**0.75**	**0.9**
Detection rate (%)	67.2	70.2	73.9	**77**	75.38

5.3 Comparaison with State of the Art Algorithms

The overall performance of our method has been compared with the following methods of the state of the art:

- Generic (Dalal and Triggs, 2005): A detector has been created in a similar way, as proposed



(a) (b)

Figure 7: Overall performance: Comparison of the specialized detector with other methods of the state of the art: (a) on the CUHK_Square dataset, (b) on the MIT traffic dataset.

by Dalal and Triggs and trained on the INRIA dataset.

- Manual Labelling: A detector has been trained on a set of labelled samples, cropped from the target video. This latter has been composed by all the pedestrians of the specialization' images and negative thumbnails that have been randomly extracted.
- Wang 2012 (Wang et al., 2012a): A specific target scene detector which has been trained on both INRIA samples and samples extracted automatically from the target scene. The selected target and the INRIA's samples are those which have had a high confidence score. The scores have been calculated using several contextual cues. The selection of training samples has been done by a new SVM variant, called "Confidence-Encoded SVM" which favors samples with a high score.
- Nair 2004 (Nair and Clark, 2004): A detector based on an automatic adaptation approach has selected the target samples to be added in the initial training dataset using the result of the background subtraction method. It is a detector similar to the detector proposed in (Nair and Clark, 2004) but it has been created with the HOG descriptor and the SVM classifier.

Figure 7.(a) shows that the specialized detector significantly exceeds the generic detector on the selected test images of the CUHK_Square dataset. The performance has improved from 26.6% to 74.37%. The specialized detector exceeds also the two other detectors of Nair 2004 and Wang 2012, respectively, by 45.57% and 23.25%. However, the target detector with manual labelling slightly exceeds the specialized detector for an FPPI of less than 0.2, but the specialized detector clearly exceeds this latter for a FPPI that is strictly greater than 0.2. In particular, it presents an improvement rate equal to 23.25% at FPPI = 1.

On the MIT Traffic dataset (Figure 7.(b)), the detection rate improves from 10% to 43%. The specialized detector even outperforms the detector trained on the target samples, labelled manually, by about 21%. Compared to Nair 2004's detector, our specialized detector gives a better detection rate than the one proposed by Nair and Clark for an FPPI less than 1. Otherwise, Nair 2004's detector slightly exceeds our specialized detector. Exceptionally, Wang 2012's detector outperforms our specialized detector by about 26%. This can be due to two facts. First, the MIT Traffic scene is very structured, which helps Wang *et al.* to get the most confident samples by using the cue of path models. Second, the video presents the shadow that makes our overlap_score unable to determine the correct positive samples.

Figure 8 shows that the specialization has considerably reduced the number of false detections and has improved the detection of some non-detected pedestrians by the generic detector. It demonstrates also the precise locations of the specialized detector.

6 CONCLUSIONS

In this paper, we have put forward a new transductive transfer learning method based on a sequential Monte Carlo filter that selects relevant samples and estimates the unknown target distribution. These samples can be used to learn a specialized classifier that importantly improves the detection performances. The suggested method has been validated on a pedestrian detection application using

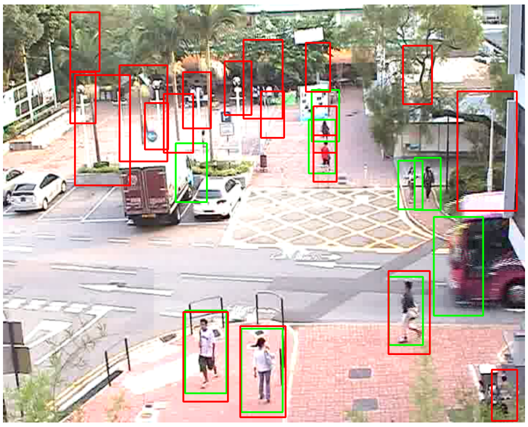


Figure 8: Illustration of the specialization result on the CUHK_Square dataset. The red bounding boxes and the green bounding boxes present the outputs of the generic and specialized detector, respectively.

the HOG-SVM classifier. The experiments have shown that the proposed specialization framework has good performances from the early iterations on two public datasets.

Future works will deal with an extension of the algorithm to a multi-object framework. Furthermore, the observation function may be ameliorated with more complex visual cues like tracking, optical flow or contextual information.

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