Incremental Domain Adaptation of Deformable Part-based Models

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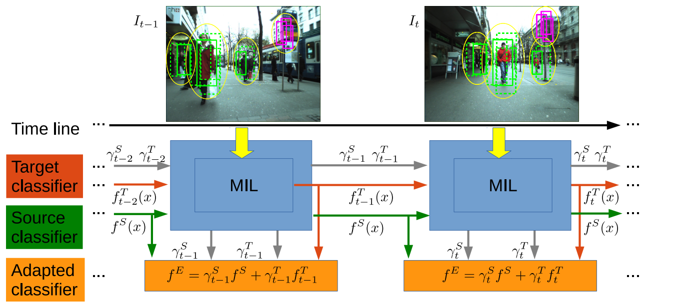

Figure 1: Incremental domain adaptation framework. $f_t^T(\mathbf{x})$ is the classifier trained by multiple instance learning (MIL) with current target image, while the final target-domain adapted classifier is f^E.

Algorithm 1 Incremental Domain Adaptation

Input:
source classifier f^S
target images $\{I_t, t \in [1,N]\}$
Output: $f^E = \gamma_N^S f^S + \gamma_N^T f_N^T$
0: $f_0^T \leftarrow f^S$, $\gamma_1^S = \gamma_1^T \leftarrow 0.5$
1: **for** t=1,2, ..., N, **do**
2: Receive image I_t, collect samples $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}$.
3: Predict $\bar{y}_j^S$ by f^S, and $\bar{y}_j^T$ by f_{t-1}^T, $j \in \{1, N_t\}$.
4: Compute γ_t^S and γ_t^T by (2).
5: Generate training bags for MIL (see Figure 1).
6: Learn f_t^T with the collected bags (Eq. (3) and Eq. (4)).
7: **end for**

In this work we focus on performing an *incremental domain adaptation* of deformable part-based model (DPM) detectors [1]. The main benefit is to have an algorithm ready to improve existing source-oriented detectors as soon as a little amount of labeled target-domain training data is available, and keep improving as more of such data arrives in a continuous fashion.

We present our adaptation model as a weighted ensemble of source- and target-domain classifiers. This model is inspired in online transfer learning (OTL) [7]. Suppose we are given a set of training samples $(\mathbf{x}_1, y_1, \mathbf{h}_1), \ldots, (\mathbf{x}_N, y_N, \mathbf{h}_N) \in \mathcal{X} \times \mathcal{Y} \times \mathcal{H}$, where $\mathcal{X}$ is the input space, $\mathcal{Y} = \{+1, -1\}$ is the label space, and $\mathcal{H}$ is the hypothesis or output space. The DPM decision function can be written as $f(\mathbf{x}) = \max_{\mathbf{h} \in \mathcal{H}} \mathbf{w}' \Phi(\mathbf{x}, \mathbf{h})$, where $\Phi(\mathbf{x}, \mathbf{h})$ is a joint feature vector.

The basic idea is to learn an ensemble classifier $f^E(\mathbf{x})$ which is a weighted combination of the source domain classifier $f^S(\mathbf{x})$ and target domain classifier $f_t^T(\mathbf{x})$ at time t of the incremental learning task. We denote by γ_t^S and γ_t^T the combination coefficients. At the time t, given a sample $\mathbf{x}$, the ensemble decision function is written as follows:

$$f^E(\mathbf{x}) = \gamma_t^S f^S(\mathbf{x}) + \gamma_t^T f_t^T(\mathbf{x}), \tag{1}$$

where $f_t^T(\mathbf{x})$ is updated incrementally each time. Note that $f^S(\mathbf{x})$ and $f_t^T(\mathbf{x})$ are not independent as they maximize over the same $\mathbf{h}$ at training and testing time. In addition to updating $f_t^T(\mathbf{x})$, the two coefficients γ_t^S and γ_t^T are adjusted dynamically. The following updating scheme can be extended from OTL [7]:

$$\gamma_t^S = \frac{\gamma_{t-1}^S g_{t-1}(\bar{y}_i^S, y_i)}{\Gamma_{t-1}}, \quad \gamma_t^T = \frac{\gamma_{t-1}^T g_{t-1}(\bar{y}_i^T, y_i)}{\Gamma_{t-1}}, \tag{2}$$

where $\Gamma_t = \gamma_t^S g_t(\bar{y}_i^S, y_i) + \gamma_t^T g_t(\bar{y}_i^T, y_i)$, $\bar{y}_i^S$ is the predicted label by f^S and $\bar{y}_i^T$ by f_{t-1}^T, $g_t(\bar{y}_i, y_i) = \frac{1}{N_t} \sum_{i=0}^{N_t} \exp\{-\frac{1}{2} l^*(\Pi(\bar{y}_i), \Pi(y_i))\}$, N_t is the number of target domain training samples at time t, $\Pi(s) = \max(0, \min(1, \frac{s+1}{2}))$ is a normalization function, and $l^*(\bar{y}, y) = (\bar{y} - y)^2$ is the square loss we use.

To train $f_t^T(\mathbf{x})$ in the target domain, we apply an incremental learning strategy similar to [2] under a frame-by-frame setting. Assume we receive an image I_t at time t and we learn f_t^T on that image by updating f_{t-1}^T learned at time $t-1$. Motivated by the online learning algorithms [3], we define f_t^T on instance $\mathbf{x}$ as follows:

$$f_t^T(\mathbf{x}) = \max_{\mathbf{h} \in \mathcal{H}} [\mathbf{w}_{t-1}' \Phi(\mathbf{x}, \mathbf{h}) + (\mathbf{w}_t' - \mathbf{w}_{t-1}') \Phi(\mathbf{x}, \mathbf{h})] = f_{t-1}^T(\mathbf{x}) + \Delta f_t^T(\mathbf{x}), \tag{3}$$

where $\Delta f_t^T(\mathbf{x})$ is the perturbation function. Given the training bags with instances $\mathbf{x}_i, \ldots, \mathbf{x}_{N_t}$, we learn the parameters $\mathbf{w}_t$ by minimizing the following objective function:

$$J(\mathbf{w}_t) = \frac{1}{2} \|\mathbf{w}_t - \mathbf{w}_{t-1}\|^2 + C \sum_{i=1}^{N_t} \mathcal{L}_{surr}(\mathbf{w}_t, \mathbf{x}_i, y_i, \mathbf{h}_i). \tag{4}$$

In some cases, the labels of target domain examples are weakly labeled, *e.g.*, pedestrian samples are collected by applying a pre-trained detector. We propose to handle weakly labeled examples by multiple instance learning (MIL) (see Figure 1), and the weakly labeled structured SVM (WL-SSVM) is used to train DPM by MIL. With the above learning strategy, f_t^T can be embedded into the OLT framework.The complete algorithm is presented in Alg. 1.

We evaluate the proposed method on several pedestrian datasets. We use a synthetic dataset [6] to train our source domain DPM detector, and adapt it to multiple real-world datasets [4, 5]. The incremental domain adaptation achieves comparable accuracy results to the batch learned model while being more flexible for learning with continuously coming target domain data. In the future, we plan to focus on improving the incremental domain adaptation with unlabeled target domain images.

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