Human Reappearance Detection Based on On-line Learning

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Abstract

Many video surveillance applications require detecting human reappearances in a scene monitored by a camera or over a network of cameras. This is the human reappearance detection (HRD) problem. Studying this problem is important for analyzing a surveillance scenario at semantic level. In this paper, we propose a novel online learning framework for solving HRD problem. Both generative model and discriminative model are employed in this framework and a voting scheme is presented to fuse the decisions of both models for determining whether a just entered person is one of those who have shown up, i.e. whether a reappearance happens. Both models will be updated based on mistake-driven online learning strategy. Our experimental results show that the adopted online learning framework not only improves the reappearance detection accuracy but also achieves high robustness in various surveillance scenes.

1. Introduction

Many video surveillance applications require determining if a newly appeared individual has been previously observed by a camera or in a camera network. This is the *human reappearance detection (HRD)* problem. *HRD* plays a key role in analyzing and understanding kinds of challenging surveillance scenarios at semantic level, including long-term human behavior analysis and abnormal behavior/event detection. It also provides solutions for many difficult problems such as resuming tracking after long-period occlusion, tracking across multiple cameras over wide areas of complicated terrain, and effectively clustering or structuring multimedia contents for retrieval.

Several approaches have been proposed to solve the *HRD* problem. In [6], Javed *et al.* proposed a method to create correspondences among observed individuals under distributed multi-camera networks using a maximum a posteriori (MAP) estimation. They assume that all models for individuals have been learned off-line beforehand. Gheissari *et al.* [4] presented an approach to create unique generative appearance models for each individual and apply these models to human reappearances detection. Spatiotemporal information is incorporated in the proposed generative model to segment human body and then create local signatures for each body segment.

In this project, we consider that the *HRD* problem is intrinsically an online learning and matching problem. This is because i) under real surveillance situations, who will enter the scene is unpredictable, so it is impossible to prepare a complete human model database beforehand. ii) Human appearance keeps changing due to variations of illumination, human pose and motion, viewing angles, and occlusion. Therefore, to solve this *HRD* problem radically, we have to 1) create human models in an online fashion; 2) adapt these models to environment and viewing angle changes by continuously updating them. These are the fundamental distinctions between our work and the previous studies, and they are also our contributions to solve the human reappearance detection problem.

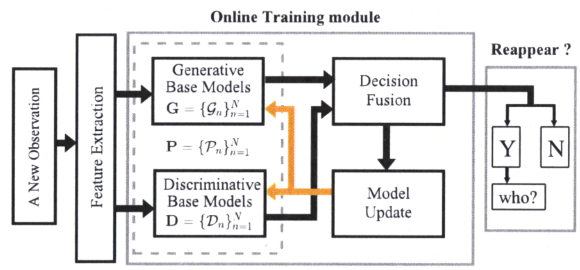

Figure 1: The sketched online learning framework. The highlighted arrow lines are model updating processes.

In this paper, we propose a novel online learning framework for this problem. Both generative model and discriminative model are created online and a voting scheme is presented to fuse the decisions of both models for determining whether a reappearance happens. Both models will be updated based on a mistake-driven online learning strategy. To better explain the framework, we sketch it in Fig.1.

In the rest of this paper, we detail our generative model and discriminative model in Section 2. In Section 3, we formulate our online learning framework, and then introduce the decision fusion scheme and the update strategy. We present and analyze the experimental results in Section 4. Finally, we summarize the paper and offer a discussion in Section 5.

2. Human Models

In this project, we adopt both generative model and discriminative model in the framework. Generative approaches often achieve better performance when training data sets are small, and they are more suitable for incremental learning. That is why most approaches on *HRD* problem merely employ

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generative models. However, compared to generative models, discriminative models usually are easier to train and they can achieve higher classification accuracy. Serval studies[11] suggest that it will be advantageous to combine these two complementary models into a hybrid framework. Therefore, we employ both models and fuse them through a voting scheme for detecting reappearances. In the following, we first introduce features we use, then discuss the two types of models in detail.

2.1 Features and Distance Metrics

Color is one of the most important cues for visual perception. We employ 2 types of color features: i) Color autocorrelogram (CAC) [5] has shown great success in image retrieval and object recognition. ii) Main color representation (MCR), proposed in [10], is demonstrated to be an effective feature for *HRD* problem. Based on the segmentation method used in [10], each person has 3 CAC histograms which are extracted from his/her upper body segment (h_1) and lower body segment (h_2), and whole body segment(h_3), respectively. Similarly we have 3 MCR histograms (h_4, h_5, h_6).

We employ a bag-of-words model [8] on SIFT descriptors [9] as a human codebook . A histogram(h_7) of the SIFT keyword distribution are adopted as another feature of a person.

All these 7 features mentioned above are employed in our generative model, and they are assumed to be independent. As all these features are in the form of distributions, *KL-divergence* is used as a metric to measure the feature distance.

$$d_i(h_i|h_i') = \sum_j h_{i,j} \log \frac{h_{i,j}}{h'_{i,j}}, \quad i = 1, \cdots, 7.$$

where $h_{i,j}$ is the jth bin height of the ith feature histogram.

Besides these features, the number of matched SIFT descriptors (d_8)is also used in our discriminative model.

2.2 Generative Model

Based on the selected features, we create a generative model $\mathcal{G}_p$ for each individual $\mathcal{P}$. The likelihood of an observation $\mathcal{O} = (h_i : i = 1, \cdots, 7)$ given the model $\mathcal{G}_p$ is defined as

$$p(\mathcal{O}|\mathcal{G}_p; \Theta_p) = e^{-\sum_{i=1}^{7} \alpha_{p,i} \cdot d_i(h_i|h_{p,i})},$$

where $\Theta_p = (\alpha_{p,i}, h_{p,i} : i = 1, \cdots, 7)$ is the model parameter. $h_{p,i}$ is person $\mathcal{P}$'s ith feature vector, which is learned via online learning introduced later. $d_i(h_i|h_{p,i})$ is the *KL-divergence* between h_i and $h_{p,i}$. $\alpha_{p,i}$ is the weight of d_i. In theory, $\alpha_{p,i}$ should be learned by maximum likelihood estimation (MLE) under maximum entropy principle, which will be very computationally expensive. In this project we simplify this procedure by computing α as

$$\alpha_{p,i} = \left[\frac{1}{\binom{n_p}{2}} \sum_{s \neq t} d_i\left(h_{p,i}^s | h_{p,i}^t\right) \right]^{-1}, \quad i = 1, \cdots, 7$$

where, n_p is the number of observations of person $\mathcal{P}$, $\binom{n_p}{2}$ is n_p choose 2, and $h_{p,i}^s$ is the ith feature of the sth observation of $\mathcal{P}$. So $\alpha_{p,i}$ is updated along with online learning process.

The generative model make the decision about whether $\mathcal{O}$ is an observation of $\mathcal{P}$ as

$$\mathcal{Y}_{\mathcal{G}_p}(\mathcal{O}) = \begin{cases} +1, & p(\mathcal{O}|\mathcal{G}_p) > \theta \\ -1, & \text{otherwise} \end{cases} \tag{1}$$

where, θ is threshold of classifier, which is selected by analyzing ROC curves discussed in Section 4.

2.3 Discriminative Model

As a counterpart of the generative model, a discriminative model $\mathcal{D}_p$ is created for each individual $\mathcal{P}$. We define $X_{o|p} = (d_i : i = 1, \cdots, 8)$ as the feature vector of $\mathcal{D}_p$. Positive examples with label +1 indicate they are sample of the same person; negative examples with label -1 indicate they are not. The discriminative model is denoted as $\mathcal{D}_p = \{y_{\mathcal{D}_p,k}, w_{p,k}\}_{k=1}^K$, where $y_{\mathcal{D}_p,k}$ is a weak classifier trained for $X_{p,k}$, and w_k is its weight which is learned by an online boosting algorithm[12]. The strong classifiers make decision about whether $\mathcal{O}$ is an observation of $\mathcal{P}$ as

$$\mathcal{Y}_{\mathcal{D}_p}(X_{o|p}) = \text{sign}\Big(\sum_{k=1}^{8} w_{p,k} \cdot y_{\mathcal{D}_p,k}\big(X_{o|p,k}\big) \Big). \tag{2}$$

We adopt *Flexible Naive Baÿes* [7] as our weak classifier. It uses *kernel density estimation* instead of single Gaussian to estimate the density of continuous distributions. The classifier is in the form

$$y_{\mathcal{D}}(x) = \text{sign}\Big(\log \frac{p(x|+1)p(+1)}{p(x|-1)p(-1)} \Big).$$

3. Online Learning Framework

3.1 Problem Formulation

We formulate the *human reappearance detection* problem in video surveillance as follows: Assume that, at a time, we have *M* observations $\mathbf{O} = \{\mathcal{O}_m\}_{m=1}^M$ of *N* identified individuals $\mathbf{P} = \{\mathcal{P}_n\}_{n=1}^N$, where $M \geq N$. When a new observation $\mathcal{O}_{M+1}$ is detected from a monitored camera, our online learning framework will proceed following the procedure shown in Fig.1: i) For each individual $\mathcal{P}_n$, both the generative model $\mathcal{G}_{p_n}$ and the discriminative model $\mathcal{D}_{p_n}$ will make decisions about whether $\mathcal{O}_{M+1}$ is a reappearance of $\mathcal{P}_n$ by Eqn.1 and Eqn.2 independently. ii)Then all the $2N$ decisions will be combined in the decision fusion module (introduced in Sec.3.2) to make the final decision. If $\mathcal{O}_{M+1}$ is a reappearance of $\mathcal{P}_i$, the system outputs $\mathcal{P}_i$; otherwise, we initiate 2 new models for this new individual $\mathcal{P}_n$ (Sec.3.3). iii) If the models give wrong decisions, they will be updated by our model update module. This is explained in Sec.3.3.

3.2 Decision Fusion

The decision fusion includes two sequential steps:

1. Fuse the two decisions of the generative model and the discriminative model of each individual. We adopt an adaptive weighted voting scheme. For each person $\mathcal{P}_n$, whether $\mathcal{O}_{M+1}$ is a reappearance of $\mathcal{P}_n$ is decided by

   $$\mathcal{Y}_{\mathcal{P}_n}(\mathcal{O}) = \text{sign}\big(\beta_n \mathcal{Y}_{\mathcal{G}_{\mathcal{P}_n}}(\mathcal{O}) + (1-\beta_n)\mathcal{Y}_{\mathcal{D}_{\mathcal{P}_n}}(X_{o|\mathcal{P}_n})\big).$$

   β_n is the weight of the generative model. The two models'decision weights are adjusted adaptively when any of them makes a wrong decision.

$$\beta_n^{t+1} = \begin{cases} \beta_n^t - \epsilon, & \text{if } \mathcal{Y}_{\mathcal{G}_{p_n}}(\mathcal{O}_{M+1}) \text{ is wrong} \\ \beta_n^t + \epsilon, & \text{if } \mathcal{Y}_{\mathcal{D}_{p_n}}(\mathcal{O}_{M+1}) \text{ is wrong} \\ \beta_n^t, & \text{otherwise} \end{cases} \tag{3}$$

We choose $\epsilon = 0.02$.

2. Combine all $\{\mathcal{Y}_{\mathcal{P}_n}\}_{n=1}^{N}$ of every individual and make a final decision about whether a reappearance occurs. If *yes*, the system outputs the reappeared individual's identity. The procedure is as follows.

   (a) If there is no reappearance, $\mathcal{O}_{M+1}$ is an observation of a new individual $\mathcal{P}_{N+1}$. Then $\mathcal{G}_{N+1}$ and $\mathcal{D}_{N+1}$ are initialized.

   (b) If there is a single positive decision, say $\mathcal{Y}_{\mathcal{P}_n}$, $\mathcal{O}_{M+1}$ is a reappearance of $\mathcal{P}_n$.

   (c) If there are multiple positive decisions of several individuals, it means that, based on the current models, the system cannot make a unique decision. In this case, $\mathcal{O}_{M+1}$ is assigned to the one who have appeared with the most times.

3.3 Update Strategy

In mistake-driven online learning algorithms, when each new example are presented, current models will make a prediction and compare it to its true label. In the case of a wrong prediction, the model will be updated. So there are 3 key issues of this type of online learning algorithm: 1) how to get true labels; 2) when to update models; and 3) how to initialize and update models. We propose solutions to these issues in our ***HRD*** online learning strategy in the following part.

About the first key issue, we can acquire a true label from the following situations:

- If multiple individuals exist in the same scene, without loss of generality, say one of the observations $\mathcal{O}_i$ is an identified person $\mathcal{P}_i$, we can be sure that other observations, say $\mathcal{O}_j$ must not be an observation of $\mathcal{P}_i$. This is individuals' *identity mutual exclusiveness* within the same scene. Using this property, we can acquire a negative example of $\mathcal{P}_i$, and its label is denoted as $\mathcal{T}_{o_j|p_i} = -1$. We call this type of inferred label "sure label".
- If a person $\mathcal{P}_i$ stays in the scene for a relatively long period, his/her appearance may be largely changed. To timely update the models, we will keep recording other observation $\mathcal{O}_k$ of him/her while tracking him/her. In this way, we can obtain a set of positive examples of $\mathcal{P}_i$ with "sure labels" $\mathcal{T}_{o_k|p_i} = +1$. At the same time, these examples are negative examples of other identified individuals, say $\mathcal{P}_j \in \mathbf{P}$, with "sure label" $\mathcal{T}_{o_k|p_j} = -1$.

Based on these obtained "sure labels", if a model makes a wrong prediction, it needs to be updated based on the following *model update strategies*.

1. If $\mathcal{T}_{o_{M+1}|p_n} = -1$ and $\mathcal{Y}_{\mathcal{P}_n}(\mathcal{O}_{M+1}) = +1$, we update β_n as Eqn.3. $X_{o_{M+1}|p_n}$ with label -1 is used as a negative example to update the discriminative model $\mathcal{D}_n$.
2. If $\mathcal{T}_{o_{M+1}|p_n} = +1$ and $\mathcal{Y}_{\mathcal{P}_n}(\mathcal{O}_{M+1}) = -1$, we update β_n as Eqn.3. $X_{o_{M+1}|p_n}$ with label +1 is used as a negative example to update the discriminative model $\mathcal{D}_n$. Meanwhile, because the true positive label suggests that $\mathcal{O}_{M+1}$ is a reappearance of $\mathcal{P}_n$, the generative model $\mathcal{G}_n$ should be updated as well.
3. As discussed before, if multiple positive decisions are made, we choose one as the right decision, i.e. the others are considered as wrong decisions. We then update models by the above two strategies under this situation.

As for the last key issue, we propose an itemized scheme to initialize and update models as follows:

Initialization. At the beginning, there are only few negative examples to a new appeared individual. As it is hard to create an effective discriminative model based on skewed training data set, we provide some random human data as negative examples to initialize the discriminative model.

Update generative models. To update a generative model with a new observation, both the CAC and MCR histograms are averaged, the SIFT keypoints are added, and the SIFT keyword distribution is recalculated.

Update discriminative models. While a new example shows up, the discriminative model is updated by an asymmetric online boosting algorithm [12].

4. Experimental Results

4.1 Data Set

Three video sequences are used to test our approach, including two CAVIAR videos[1] and one self-shot video. These videos are of 3 different surveillance scenes captured under various illumination conditions: under daylight, at dusk and indoor. There are 76 individuals and 88 reappearances in total in these video sequences. Besides, the bag-of-word model is trained on Penn-Fudan Pedestrian database [2].

4.2 A Baseline Model

In this experiment, to compare our approach, we propose a typical baseline model, which combines an ensemble of weak classifiers trained on-line by AdaBoost [3] to determine whether a reappearance occurs. The "sure labels" of examples for the ensemble are obtained in the same way described in this paper. However, the only discriminative model is periodically updated. And a newly trained weak classifier is used to substitute for the worst one along the time.

4.3 Experiments and Results

We compare the performances of our method with the baseline model in Tab.1. In this experiment, $\theta = 0.38$, and the initial value of $\beta = 0.6$. As Tab.1 shows, our online learning framework not only achieves higher accuracy than the other, but also is more robust in different surveillance environments: the reappearances rate is low in the corridor sequence. Thus, the data for the discriminative classifiers are very skewed. However, accuracy of our approach is still high compared with the baseline model. This robustness is due to the combination of the generative model and the discriminative models in the online learning process. Two results in a corridor scene and a road scene are shown in Fig.2.

In Tab.2, it shows that the number of model update occurred in our approach is much less than that of the baseline model. This is because that our approach only updates models whenever necessary, *i.e.* when wrong prediction happens. Meanwhile, shorter runtime indicate that our new approach

Figure 2: Results of our approach in two scenes. The red rectangles highlight that reappearances are detected.

Scene	n_p	n_r	baseline(%)	our approach(%)
Road	8	20	94.0%	**95.9%**
Corridor	58	38	70.4%	**87.5%**
Doorway	10	30	85.9%	**90.3%**

Table 1: Classification accuracy comparison between baseline method and online learning strategy. n_p denotes the number of individuals who appear in the scene, while n_r denotes the number of reappearances.

method	update number	runtime
our approach/baseline	**23**/120	**3**/ 12 min

Table 2: Performance comparison between the 2 approaches.

updates models more lightly. So that it can be applied to a realtime scenario.

ROC curve is an important tool for comparing performance of classifiers. In our approach, we adjust the threshold θ and the initial weight β of generative models to compute the ROC curve. The values of θ and β used in the former experiment are chosen according to this ROC curve as well. The comparison results are shown in Fig.3(a). It is obvious that our approach achieves better performance.

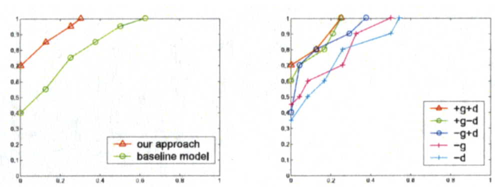

Figure 3: Comparison of ROC curves.

We also compare the ROC curves of our approach, the combined models which are online updated (+g+d), with the other cases: update generative models alone(+g-d), update discriminative models alone (-g+d), only use not-updated generative models (-g), and only use not-updated discriminative models (-d). From Fig.3(b), we can draw the following conclusions:

1. Combination of the generative model with discriminative model is superior to either models alone.
2. Updated models perform better than not-updated models, which strongly suggests that our online learning strategy is a necessity to solve the *HRD* problem.

5. Summary and Discussion

In this paper, we present a novel online learning framework for *human reappearance detection* problem. It combines both generative model and discriminative model to determine whether a reappearance occurs. Both models are updated based on a mistake-driven online learning strategy. Compared to the baseline model, our approach achieves higher accuracy and better robustness in various surveillance scenes.

To further our approach, the following considerations can be taken into account:

1. We exploit "sure information" from scenes to assist efficient and effective model update. This information is consonant with *must-links* and *cannot-links* in *semi-supervised clustering (SSC)*. It is reasonable to formulate *HRD* into an online *SSC* problem.
2. When multiple positive decisions are made to an observation by the individual models (discussed in Sec.3.2 Step 2.(c)), it is unreliable to get its true label. Interactive methods can be adopted to effectively handle this case.
3. Employing more robust features and temporal information may improve the performance of our method.

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