Robust Feature Selection Approach for Object Tracking

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Abstract – Most tracking-by-detection algorithms train discriminative classifiers to separate target objects from their surrounding background, In this setting, noisy samples are likely to be included when they are not properly sampled, thereby causing visual drift. The multiple instances learning (MIL) learning paradigm has treen recently applied to alleviate this problem. However, important prior information of instance labels and the most correct positive instance (i.e., the tracking result in the current frame) can be exploited using a novel formulation much simpler than an MIL approach. In this paper, it shows that integrating such prior information into a supervised learning algorithm can handle visual drift more effectively and efficiently than the existing MIL tracker. It present an online discriminative feature selection algorithm which optimizes the objective function in the steepest ascent direction with respect to the positive samples while in the steepest descent direction with respect to .the negative ones. Therefore, the trained classifier directly couples its score with the importance of samples, leading to a more rotrust and efficient tracker. Numerous experimental evaluations with state-of-the-art algorithms on challenging sequences demonstrate the merits of the proposed algorithm.

Keywords – Object Tracking, Multiple Instance Learning, Supervised Learning, Online Boosting, ODFS Tracker, Classifier.

I. INTRODUCTION

Object tracking has been extensively studied in computer vision due to its importance in applications such as automated surveillance, video indexing, traffic monitoring, and human-computer interaction, to name a few. While numerous algorithms have been proposed during the past decades, it is still a challenging task to build a robust and efficient tracking system to deal with appearance change caused by abrupt motion, illumination variation, shape deformation, and occlusion. It has been demonstrated that an effective adaptive appearance model plays an important role for object tracking. In general, tracking algorithms can be categorized into two classes based on their representation schemes: generative and discriminative models .Generative algorithms typically learn an appearance model and use it to search for image regions with minimal reconstruction errors as tracking results. To deal with appearance variation, adaptive models such as the WSL tracker and IVT method have been proposed. Adam et al. utilize several fragments to design an appearance model to handle pose change and partial occlusion. Recently, sparse representation methods have been used to represent the object by a set of target and trivial templates to deal with partial occlusion,

illumination change and pose variation. However, these generative models do not take surrounding visual context into account and discard useful information that can be exploited to better separate target object from the background. Discriminative models pose object tracking as a detection problem in which a classifier is learned to separate the target object from its surrounding background within a local region. Collins et al. demonstrate that selecting discriminative features in an online manner improves tracking performance. Boosting method has been used for object tracking by combing weak classifiers with pixel-based features within the target and background regions with the oncenter off-surround principle. However, the above_ mentioned discriminative algorithms utilize only one positive sample (i.e., the tracking result in the current frame) and multiple negative samples when updating the classifier. If the object location detected by the current classifier is not precise, the positive sample will be noisy and result in a suboptimal classifier update. Consequently, errors will be accumulated and cause tracking drift or failure. To alleviate the drifting problem, an online semi supervised approach is proposed to train the classifier by only labeling the samples in the first same while considering the samples in the other frames as unlabeled.

Recently, an efficient tracking algorithm based on compressive sensing theories is proposed. It demonstrates that the low dimensional features randomly extracted from the high dimensional multi scale image features preserve the intrinsic disctiminative capability, thereby facilitating object tracking. Several tracking algorithms h; been developed within the multiple instance learning (MIL) flame works in order to handle location ambigiities of positive samples for object tracking. In this paper, it demonstrate that it is unnecessary to use feature selection method proposed in the tvttL tracker and instead an efficient feature selection method based on optimization of the instance probability can be exploited for better performance. Motivated by success of formulating the face detection problem with the multiple instance learning framework, an online multiple instance learning method is proposed to handle the ambiguity problem of sample location by minimizing the bag likelihood loss function. It notes that in the MILES model is employed to select features in a supervised learning manner for object tracking. However, this method runs at abofi 2 to 5 frames per second (FPS), which is less efficient than the proposed algorithm (about 30 FPS). In addition, this method is developed with the MIL framework and thus has similar

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drawbacks as the MIL Track method. Recently, Hare etal. Show that the objectives for tracking and classification are not explicitly coupled because the objective for tracking is to estimate the most correct object position while the objective for classification is to predict the instance labels. However, this issue is not addressed in the existing discriminative tracking methods under the MIL framework. In this paper propose an efficient and robust tracking algorithm which addresses all the above-mentioned issues. The key contributions of this work are summarized as follows.

1) A simple and effective online discriminative feature selection (ODFS) approach which directly couples the classifier score with the sample importance, thereby formulating a more robust and efficient tracker than state-of-the-art algorithms and 17 times faster than the MIL Track method (both are implemented in MATLAB).

2) It is unnecessary to use bag likelihood loss functions for feature selection as proposed in the MIL Track method. Instead, it can directly select features on the instance level by using a supervised learning method which is more efficient and robust than the MIL Track method. As all the instances, including the correct positive one, can be labeled from the current classifier, they can be used for update via self-taught learning [25]. Here, the most correct positive instance can be effectively used as the tracking result of the current frame in a way similar to other discriminative models

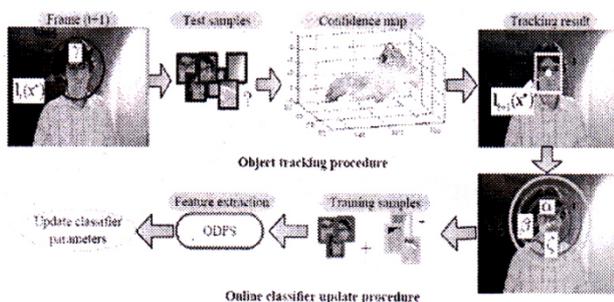## II. ON LINE DISCRIMINATIVE FEATURE SELECTION

Fig. ODFS tracker

A. Tracking by Detection

Figure illustrates the basic flow of algorithm. The discriminative appearance model is based at classifier which estimates the posterior probability given a classifier, the tracking by detection process is as follows. Let the location of sample at frame. The object location where assume the corresponding sample and then densely arop some patches within a search radius centering at the current object location and label them as positive samples. Then, randomly crop some patches from set and label them as negative samples. It utilizes these samples to update the classifier. When the frame arrives, it crop some

patches with a large radius surrounding the old object location frame. Next, apply the updated classifier to these patches to find the patch with the maximum confidence. The location is the new object location in the frame. Based on the newly detected object location, tracking system repeats the above-mentioned procedures.

B. Classifier Construction and L/pdate

In this sample is represented by a feature vector where each feature is assumed to be independently distributed as MIL Track and then the classifier can be modeled by a naive Bayes classifier is a weak classifier with equal prior. Next, the classifier is a linear function of weak classifiers and uses a set of Haar-like features [5] to represent samples. The conditional distributions and in the classifier are assumed to be Gaussian distributed as the MIL Track method [15] with four parameters.

The parameters are incrementally estimated and N is the number of positive samples. In addition update and with similar rules. It can be easily deduced by maximum Iikelihood estimation method where learning rate to moderate the balance between the former frames and the current one. It should be noted that parameter update method is different from that of the MIL Track method and it can be update equations are derived based on maximum likelihood estimation. For online object tracking, a feature pool with M > K features is maintained. As demonstrated in online selection of the discriminative features between object and background can significantly improve the performance of tracking. The objective is to estimate the sample with the maximum confidence from as with K selected features. However, directly select K features fiom the pool of M features by using a brute force method to maximize the computational complexity with combinations is prohibitively high (set t< : l5 and M : 150 in 'experiments) for real-time object tracking. An efficient online discriminative feature selection method which is a sequential forward selection method where the number of feature combinations is MK, thereby facilitating real-time performance.

C. Principle of ODFS:

The confidence map of a sample being the target is cornputed, and the object location is determined by the peak of the map. Providing that the sample space is partitioned into two regions it defines a margin as the average confidence of samples in minus the average confidence of samples. Cardinalities of positive and negative sets.

In the training set, assume the positive set consists of N samples, and the negative set is composed of L samples .Each sample is represented by a feature vector. A weak classifier pool is maintained using objective is to select a subset of weak classifiers from the pool which maximizes the average confidence of samples in while suppressing the average confidence of samples. Therefore, maximize the margin function. Use a greedy scheme to sequentially select one weak classifier from the pool to maximize. A

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classifier constructed by a linear combination of the first weak classifiers. Note that it is difficult to find a closed form solution of the objective function in Furthermore, although it is natural and easy to directly select that maximizes objective function in the selected is optimal only to the current samples, which limits its generalization capability for the extracted samples in the new frames.

An approach similar to the approach used in the gradient boosting method to solve which enhances the generalization capability for the selected weak classifiers. The steepest descent direction of the objective function of in the (N+L) dimensional data space at the inverse gradient (i.e., the steepest descent direction) of the posterior probability function, its generalization capability is limited. Friedman proposes an approach to select that makes most parallel to when minimizing objective function in. The selected weak classifier is most highly correlated with the gradient over the data distribution, thereby improving its generalization performance. In this work, instead select that is least parallel to as maximize the objective function Thus, choose the weak classifier with the following criterion which constrains the relationship between Single Gradient and Single weak Classifier (SGSC) output for each sample. However, the constraint between the selected weak classifier and the inverse gradient direction is still too strong in because is limited to the small pool.

In addition, both the single gradient and the weak classifier output are easily affected by noise introduced by the misaligned samples, which may lead to unstable results. To alleviate this problem, relax the constraint and with the Average Gradient and Average weak Classifier (AGAC) criteria in a way similar to the regression tree method in That is, take the average weak classifier output for the positive and negative samples, and the average gradient direction instead of each gradient direction for every sarnple, However, this pooled variance is easily affected by noisy data or outliers. This means the selected weak classifier tends to maximize while suppressing the variance thereby leading to more stable results.

In this a small search radius is adopted to crop out the positive samples in the neighborhood of the current object location, leading to the positive samples with very similar appearances. Therefore, the ODFS criterion becomes it is worth noting that the average weak classifier output computed from different positive samples alleviates the noise effects caused by some misaligned positive samples. Moreover, the gradient from the most correct positive sample helps select effective features that reduce the sample ambiguity problem. In contrast, other discriminative models that update with positive features from only one positive sample are susceptible to noise induced by the misaligned positive sample when drift occurs. If only one positive sample (i.e., the tracking result) is used for feature selection in this method, the single positive feature selection (SPFS) criterion it present

experimental results to validate why the proposed method performs better than the one using the SPFS criterion. When a new liame arrives, it updates all the weak classifiers in the pool in parallel and select K weak classifiers sequentially from using the criterion. The main steps of the proposed online discriminative feature selection algorithm.

D. Algorithm: Online discriminative feature selection:

l. Input: dataset
2. Update weak classifier pool
3. Update the average weak classifier outputs
4. Update inverse gradient.
5. Correlate gradient and classifier.
6. Calculate average weak classifier output.
7. Normalize classifier
8. Output : strong classifier and confidence map function

III. COMPARISON OF ODFS AND MIL TRACKING

ODFS tracker selects 15 features for classifier construction which is much more efficient than the MIL Track method that sets K : 50. The number of candidate features M in the feature pool is set to 150, which is fewer than that of the MIL Track method (M : 250). It note that also evaluate with the parameter settings K : 15; M : 150 in the MIL Track method but find it does not perform well for most experiments. The learning parameter can be set .A smaller learning rate can make the tracker quickly adapts to the fast appearance changes and a larger leaming rate can reduce the likelihood that the tracker drifts off the target. Good results can be achieved.

Use a radius of 4 pixels for cropping the similar positive samples in each frame and generate 45 positive samples. A large can make positive samples much different which may add more noise but a small generates a small number of positive samples which are insufficient to avoid noise.

The inner and outer fadii for the set that generates negative samples are set. Set the inner radius larger than the radius to reduce the overlaps with the positive samples which can reduce the ambiguity between the positive and negative samples.

Then randomly select a set of 40 negative samples from the set which is fewer than that of the MIL Track method (where 65 negative examples are used). It does not need to utilize many samples to initialize the classifier whereas the MIL Track method uses 1000 negative patches. The radius for searching the new object location in the next frame is set as : 25 that is enough to take into account all possible object locations because the object motion between two consecutive frames is often smooth, and 2000 samples are drawn, which is the same as the MIL Track method. Therefore, this procedure is time-consuming use more features in the classifier design.

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IV. CONCLUSION

In this paper we have presented a tracking system called MIL Track that uses a novel Online Multiple Instanbe Learning algorithm. The MIL framework allows us to update the appearance model with a set of image patches, even though it is not known which image patch precisely captures the object of interest. This leads to more robust tracking results with fewer parameter tweaks. It would be interesting to extend this system to be part based like, which could further improve the performance with the presence of severe occlusions. A part-based model could also potentially reduce the amount ofdrift by better aligning the tracker location with the object. Finally we are interested in other possible applications for our online Multiple Instance Learning algorithm. In this present a novel online discriminative features election (ODFS) method for object tracking which couples the classifier score explicitly with the importance of the samples. The proposed ODFS method selects features which optimize the classifier objective function in the steepest ascent direction with respect to the positive samples while in steepest descent direction with respect to the negative ones. This leads to a more robust and efficient tracker without parameter tuning, Basically MIL tracker deals with single image patch or sample. And ODFS- deals with set of image patches or sample.

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