Point-to-Set Distance Metric Learning on Deep Representations for Visual Tracking

Shengping Zhang, Yuankai Qi, Feng Jiang, Xiangyuan Lan, Pong C. Yuen, and Huiyu Zhou

Abstract—For autonomous driving application, a car shall be able to track objects in the scene in order to estimate where and how they will move such that the tracker embedded in the car can efficiently alert the car for effective collision-avoidance. Traditional discriminative object tracking methods usually train a binary classifier via a support vector machine (SVM) scheme to distinguish the target from its background. Despite demonstrated success, the performance of the SVM based trackers is limited because the classification is carried out only depending on support vectors (SVs) but the target's dynamic appearance may look similar to the training samples that have not been selected as SVs, especially when the training samples are not linearly classifiable. In such cases, the tracker may drift to the background and fail to track the target eventually. To address this problem, in this paper, we propose to integrate the point-to-set/image-to-imageSet distance metric learning (DML) into visual tracking tasks and take full advantage of all the training samples when determining the best target candidate. The point-to-set DML is conducted on convolutional neural network features of the training data extracted from the starting frames. When a new frame comes, target candidates are first projected to the common subspace using the learned mapping functions, and then the candidate having the minimal distance to the target template sets is selected as the tracking result. Extensive experimental results show that even without model update the proposed method is able to achieve favourable performance on challenging image sequences compared to several state-of-the-art trackers.

Index Terms—metric learning, point to set, visual tracking.

I. INTRODUCTION

VISUAL tracking has been attracting increasing interest in the past years [1]–[12] due to its important role in a wide range of applications such as video surveillance, visual reality, computer-human interaction, and autonomous driving, just to name a few. Among these applications, autonomous driving has various complications where moving targets are often mixed with significant background clutters. In addition, the measurement streams evolve in a complicated environment due to constantly changing appearance, severe occlusions and noise. Given a target in the first frame (usually in the format of a rectangle), its goal is to estimate the target states (e.g. position, scale, and rotation) throughout the remaining image frames. Despite lots of efforts have been devoted to

visual tracking during the past decades, it still remains a challenging task due to distractions such as heavy occlusions, drastic illumination variations, large scale changes, out-of-plane rotations, fast motion, and severe camera shaking.

Broadly speaking, most of the existing tracking methods fall into either the generative or discriminative category. The generative methods cast object tracking as a searching task to find the best object candidate that is best represented by the target appearance model. Many methods have been proposed to robustly model the target appearance and account for illumination changes, occlusions, and view changes. Ross *et al.* [13] proposed to use the incremental subspace learning to adapt to target appearance changes. In [14], holistic sparse coding was introduced into visual tracking, where each positive dictionary item is a whole target template and trivial items are used to account for occlusions. Despite achieving good results, the holistic sparse model is not flexible enough to represent local variations of the target. To handle this problem, Jia *et al.* [15] proposed a local sparse coding based tracking method, where each dictionary item is a part region of the target template. As evidenced by their results, this scheme is able to encode the target appearance variations more flexibly and therefore obtains better performance. Later, a two-stage sparse coding strategy was proposed in [16] to combine the advantages of both the holistic and the local sparse coding models in order to obtain better performance. On the other hand, the discriminative methods formulate object tracking as a binary classification task, where the target region is viewed as the foreground and the remaining region is the background. These methods mainly focus on designing either discriminative features or powerful classifiers. For example, Danelljan *et al.* [17] proposed an adaptive low-dimensional feature based on color attributes, which is effective for color videos but not for black-white ones. In [9], the authors proposed an adaptive hedging method to combine different hierarchical features extracted from a deep convolutional neural network (CNN) and achieve reasonably better results than using only one type of feature. Different from these approaches, Hare *et al.* [18] proposed a novel classifier based on a kernelized structured output support vector machine (SVM), which directly embeds target positions into the objective function. Zhang *et al.* [19] designed a multi-expert tracking framework, which is able to filter out the appropriate expert with the most discriminative capability. More recently, several end-to-end CNN based tracking methods have been proposed, e.g. [10], [11], [20], to simultaneously learn discriminative features and effective classifiers.

Although recent discriminative tracking methods (e.g. [18], [19], [21]) usually obtain better results than generative ones,

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Fig. 1. Main steps of the proposed point-to-set distance metric learning based tracking algorithm. Target and background templates are randomly sampled from the starting frame. Then, we employ a pretrained CNN to compute their features. Based on the CNN features, these samples are divided into several target template sets and background template sets using a standard K-means method. Point-to-set distance metric learning (DML) is then performed on these sets (Section III-B). When a new frame comes, target candidates are randomly sampled and are projected to the common subspace using learned mapping functions. The candidate with the minimal distance to the target template sets is selected as the tracking result (Section III-D).

their performance is limited by the usage of SVMs. Because the SVMs determine the label of one test sample, only depending on the support vectors (SVs), the test sample may not always be correctly classified via SVs, especially when the training samples are not linearly classifiable. In such cases, the tracker may fail to find the best target candidate and therefore suffer from the tracking drift problem.

To address the above mentioned issue, we propose to take full advantages of all the training samples, instead of depending on only a few SVs, to measure the similarity between each target candidate and all the positive samples and the negative samples respectively via point-to-set distance metric learning. Specifically, we first cluster positive samples into several positive sets via K-means and cluster negative samples into negative sets in the same way to enhance the representative ability of each set. Then, for each training set we compute its mean feature vector of all the samples of that set, called *mean sample*. These mean samples represent the average appearances of the target and the background. We aim to learn mapping functions so as to pull the point-set pair with the same label close to each other and push far away otherwise. Since a mean sample can be viewed as a point in the high-dimensional Euclidean space and a sample set can be treated as a point on the Riemannian manifold, the above procedure can be formulated as mapping heterogeneous points on Euclidean space and Riemannian manifold into a common subspace. At the testing stage, all target candidates will firstly be projected onto the common subspace with the learned mapping functions and then the best target candidate

is determined with a minimum distance to the positive sets. The main steps of the proposed point-to-set distance metric learning based tracking algorithm is illustrated in Figure 1.

The main contributions of this work are in two-fold:

- 1) **We formulate the object tracking task as a point-to-set distance metric learning problem to take full advantages of all training samples.**
- 2) Numerous experimental results on a large amount of challenging image sequences demonstrate the effectiveness of the proposed tracking method.

The remaining of this paper is organized as follows. In Section II, we present a discussion on the related work. In Section III, we give a detailed description of the proposed point-to-set metric learning based tracking algorithm. Then, we extensively evaluate the proposed tracker in Section IV. Finally, we conclude the work in Section V.

II. RELATED WORK

In this section, we briefly review some related visual tracking methods, which utilize convolutional neural networks (CNNs), distance metric learning (DML), sparse coding, and multiple cues for robust visual tracking.

With the great success of CNNs on tasks such as image classification [22]–[25], natural language processing [26], [27], object detection [28]–[30], and image segmentation [31], [32], several trackers based on CNNs have been proposed. Fan *et al.* [33] pre-train a network using the location and the appearance information of the object of interest to extract

both spatial and temporal features. Hong *et al.* [34] learnt a discriminative appearance model using the CNN features of hidden layers and construct a target saliency map to help locate the target using the back-projecting CNN features. In [20], Wang *et al.* proposed a CNN architecture with two branches to simultaneously exploit high-level category information features captured by a top layer and low-level structure features captured by a lower layer. Nam and Han [10] designed a multi-domain neural network to learn common representations using shared bottom layers and to learn discriminative representations using the top layer. Different from these CNN based trackers, which either use features extracted from only one layer or treat features extracted from different layers equally, Qi *et al.* [9] proposed an ensemble tracker that adaptively combines features extracted from as many as six different layers.

Many distance metric learning based trackers have been proposed to replace traditional hand-crafted metrics, such as the Euclidean distance, to better adapt to appearance variations. Wu *et al.* [35] learnt a distance metric over sparse representations of positive and negative training samples, which are further divided into several bags. However, they use the average distance of sample pairs from different bags as the distance between the corresponding bags, which incurs a high computational cost. Jiang *et al.* [2] used the sparsity regularization in metric learning to find the lowest possible dimensionality of the projection and thus to reduce the computational cost and also keep the best discriminative ability. In [36], Wang *et al.* unified the appearance modeling and visual matching using one objective in the formulation of metric learning to well capture the manifold structure of the discriminative appearances. In [1], Jiang *et al.* extended the linear metric to a nonlinear one using the RBF-kernel, and their training samples are collected on-the-fly, which makes the learned metric adaptive to appearance variations. Although the aforementioned DML based trackers improve the performance to some extent, they are still limited to the point-to-point/image-to-image metric learning. This not only incurs large computational cost but also may lead to visual mismatching when large appearance variation occurs. In this paper, we alleviate these problems by introducing the point-to-set/image-to-imageSet distance metric learning into visual tracking.

Besides the above mentioned approaches, there are also some methods that utilize multiple cues or learned representations to handle complex tracking scenarios. Optical flow, color, and depth clues are simultaneously incorporated in [37]. Edge information, intensity, and color features are combined into a discriminative one in [38]. Fang *et al.* [39] adds geometry constraint and attention selection to help associate tracklets. In [40], [41], both the RGB color and the depth information are combined to improve the performance of tracking. To obtain effective object representations, sparse coding and dictionary learning are used in [42]–[44]. He *et al.* [45] formulate association of two observations as a data association problem based on the spatial-temporal constraint that the trajectories of different objects must be disjoint.

III. PROPOSED ALGORITHM

In this section, we first give a brief description of some background of metric learning over Riemannian manifolds to put our method in a proper context. Then, we detail the proposed point-to-set distance metric learning based tracking algorithm.

A. Background

In the community of computer vision, a set of images can be treated as a point on the Symmetric Positive Definite (SPD) matrix manifold [46], Grassmannian manifold [47], or Affine Grassmannian manifold [48] depending on its representation in the usage of covariance matrices, linear subspaces, or affine subspaces, respectively. A prominent difference among these manifolds is the Riemannian metric over distance. In this paper, we base our algorithm on the SPD matrix manifold due to its better performance on point-to-set classification tasks than the other two as demonstrated in [49]. Let Sym_D^+ denote the Riemannian manifold that has a Riemannian metric over the space of $(D \times D)$ -dimensional symmetric positive definite matrices. According to the Log-Euclidean Distance [50], the distance between two points $P_i, P_j \in \mathbb{R}^{D \times D}$ on the manifold Sym_D^+ is defined as

$$d(P_i, P_j) = \|\log(P_i) - \log(P_j)\|_F, \quad (1)$$

which is a true geodesic distance expressed by Euclidean computations. Classical Mahalanobis Distance is usually used to define the distance between an Euclidean point x_i and a set P_j

$$d(x_i, P_j) = \sqrt{(x_i - m_j)^\top P_j^{-1} (x_i - m_j)}, \quad (2)$$

where m_j is the mean of all the samples in the dataset and P_j resides on the Sym_D^+ manifold.

B. Learning Point-to-Set Distance Metric for Visual Tracking

Let $X^+ = \{x_1^+, \dots, x_m^+\} \subset \mathbb{R}^D$ denote m target templates in the form of vectorized features, and $X^- = \{x_1^-, \dots, x_n^-\} \subset \mathbb{R}^D$ denote n background templates. These templates are extracted from the first frame of an image sequence at the beginning of tracking. A template having an overlap larger than 0.7 with the ground truth region is viewed as a target template. In contrast, a template having an overlap less than 0.5 is treated as a background template, which helps exclude incomplete target candidates.

Different from an SVM classifier, where only support vectors contribute to measuring the target candidates, in this paper, we introduce to learn a point-to-set distance metric [49] to take full advantage of all the training samples. To this end, we first cluster training templates into several sets, so that both the target and the background can be comprehensively described by representative appearances. Then, we learn the mapping functions that map Euclidean points and Riemannian manifold points into a common subspace. Because the gap between these two kinds of points are too large to bridge directly, we first project them to their own Hilbert spaces and then map to the common subspace, as shown in Figure 2.

Fig. 2. Illustration of two-step point-to-set distance metric learning, where the original heterogeneous points are first mapped onto their own Hilbert space, and then map to the common subspace.

1) *Constructing training data:* We employ the traditional clustering method K-means to cluster the target templates in X^+ into m_k sets denoted by $S^+ = \{S_1^+, \dots, S_{m_k}^+\}$ so as to minimize the within-cluster sum of squares of Euclidean distance of each point in the cluster to its cluster center

$$\arg \min_{S^+} \sum_{i=1}^{m_k} \sum_{x \in S_i^+} \|x - \mu_i\|^2, \quad (3)$$

where μ_i is the mean of points in S_i^+ . For each cluster, its mean vector is computed as its corresponding point in the Euclidean space, which is

$$e_i^+ = \frac{1}{|S_i^+|} \sum_{x \in S_i^+} x, \quad (4)$$

where $|S_i^+|$ is the number of elements in set S_i^+ . We totally obtain m_k such Euclidean points denoted from e_1^+ to $e_{m_k}^+$. The set S_i^+ and its corresponding Euclidean point e_i^+ are given the same label l_i^+ . Similarly, we cluster the background templates X^- into n_k sets denoted by $S^- = \{S_1^-, \dots, S_{n_k}^-\}$ and we compute their corresponding points in the Euclidean space denoted by $e_1^-, \dots, e_{n_k}^-$. The label is accordingly denoted by $l_1^-, \dots, l_{n_k}^-$. To embed the target sets in S^+ and background sets in S^- into Sym_D^+ manifold, each set is represented by its covariance matrix and is still denoted by the same symbol for simplicity from now on. Finally, we let $S = S^+ \cup S^-$ denote the union of S^+ and S^- .

2) *Objective formulation:* With the above prepared training data, now we learn the mapping functions shown in Figure 2 to project these heterogeneous points into a common subspace by

$$\arg \min_{f, \varphi} \lambda_1 G_{er} + \lambda_2 (G_e + G_r) + \lambda_3 R, \quad (5)$$

where G_{er} is the constraint item defined on points projected from Euclidean space and Riemannian manifold Sym_D^+ , G_e

is the constraint on points projected from Euclidean space, G_r is the constraint on points projected from Riemannian manifold Sym_D^+ , and R is the regularization item. The parameters λ_1 , λ_2 , and λ_3 control the trade-off among these three constraint items. Next, we detail these constraint items one by one.

Geometry constraint on points projected from heterogeneous spaces: G_{er} is defined to minimize the distance among points with the same label but projected from Euclidean space and Riemannian manifold Sym_D^+ respectively:

$$G_{er} = \frac{1}{2} \sum_{i=1}^{m_k+n_k} \sum_{j=1}^{m_k+n_k} \mathbf{1}(i, j) \|f(x_i) - \varphi(S_j)\|^2, \quad (6)$$

where $x_i \in X^+ \cup X^-$, $S_j \in S^+ \cup S^-$, $\mathbf{1}(i, j) = 1$ if x_i and S_j have the same label, and otherwise $\mathbf{1}(i, j) = -1$. This constraint ensures that points with the same label in heterogeneous space will be close to each other after the projection and the points will have a large distance if they are with different labels.

Geometry constraint on points projected from homogeneous spaces: The above item G_{er} only constrains the geometry relation of points mapped from heterogeneous space. However, the geometry relation of points from homogeneous spaces should also be taken into consideration. For that, we exert the following geometry constraints:

$$G_e = \frac{1}{2} \sum_{i=1}^{m_k} \sum_{j=1}^{m_k} \mathbf{d}(x_i, x_j) \|f(x_i) - f(x_j)\|^2, \quad (7)$$

$$G_r = \frac{1}{2} \sum_{i=1}^{n_k} \sum_{j=1}^{n_k} \mathbf{d}(S_i, S_j) \|f(S_i) - f(S_j)\|^2, \quad (8)$$

where $\mathbf{d}(v_i, v_j) = \exp(\|v_i - v_j\|^2 / \sigma^2)$ if v_i and v_j are with the same label and they are k_1 neighborhood of one of them, v denotes x or S . If v_i and v_j have different labels but are k_2 neighborhood of one of them, $\mathbf{d}(v_i, v_j) = -\exp(\|v_i - v_j\|^2 / \sigma^2)$. For other cases, we define $\mathbf{d}(v_i, v_j) = 0$.

Regularizer item R : After projecting these heterogeneous points into a common subspace, the Euclidean distance will be employed as the measure metric. Thus, it is reasonable to equally treat all dimensions of these projected points. To this end, we impose the following constraint:

$$R = \frac{1}{2} \left(\sum_{i=1}^{m_k+n_k} \|f(x_i)\|^2 + \sum_{j=1}^{m_k+n_k} \|\varphi(S_j)\|^2 \right). \quad (9)$$

C. Optimization

Although finding the global optimal solution for the objective function Eq. 5 is intractable, we can seek an approximate optima using the alternative iterative optimization method as shown in [49], which is capable of yielding desirable results as demonstrated in experiments. Let $\varphi_x(x_i) = V_x^\top x_i$, $\varphi_s(S_i) = V_s^\top S_i$. Then, by using the kernel trick, we get $\varphi_x(f_x(x_i)) = V_x^\top f_x(x_i) = \sum_j W_x^\top f_x(x_j) f_x(x_i) = W_x^\top K_x(\cdot, x_i)$, where $K_x(x_i, x_j) = \langle f_x(x_i), f_x(x_j) \rangle$. Similarly, we can get $\varphi_s(f_s(S_i)) = W_s^\top K_s(\cdot, i)$, where $K_s(S_i, S_j) = \langle f_s(S_i), f_s(S_j) \rangle$. With these notations, the

constraint items in Eq. 5 can be re-formulated in the matrix format:

$$G_{er}(W_x, W_s) = \frac{1}{2}(W_x^\top K_x \hat{B}_x K_x^\top W_x + W_s^\top K_s \hat{B}_s K_s^\top W_s - 2W_x^\top K_x Z K_s W_s^\top), \quad (10)$$

$$\begin{aligned} G_e(W_x) &= W_x^\top K_x B_x K_x^\top W_x - W_x^\top K_x Z_x K_x^\top W_x \\ &= W_x^\top K_x L_x K_x^\top W_x, \end{aligned} \quad (11)$$

$$\begin{aligned} G_r(W_s) &= W_s^\top K_s B_s K_s^\top W_s - W_s^\top K_s Z_s K_s^\top W_s \\ &= W_s^\top K_s L_s K_s^\top W_s, \end{aligned} \quad (12)$$

where $\hat{B}_x, \hat{B}_s, B_x$ and B_s are diagonal matrices with

$$\begin{aligned} \hat{B}_x(i, i) &= \sum_{j=1}^{n_k} \mathbf{1}(i, j), \quad \hat{B}_s(i, i) = \sum_{j=1}^{m_k} \mathbf{1}(j, i), \\ B_x(i, i) &= \sum_{j=1}^{m_k} \mathbf{d}(x_i, x_j), \quad B_s(i, i) = \sum_{j=1}^{n_k} \mathbf{d}(S_i, S_j). \end{aligned} \quad (13)$$

Let v denotes x or S , if $l_i^v = l_j^v$ and v_i and v_j are k_1 neighborhood, $Z_v(i, j) = \mathbf{d}(i, j)$; if $l_i^v \neq l_j^v$ and v_i and v_j are k_2 neighborhood, $Z_v(i, j) = -\mathbf{d}(i, j)$; otherwise, $Z_v(i, j) = 0$. Then, the object function Eq. 5 can be re-written as function of W_x and W_s :

$$\arg \min_{W_x, W_s} \lambda_1 G_{er}(W_x, W_s) + \lambda_2 (G_e W_x + G_r W_s) + \lambda_3 R. \quad (14)$$

Given an initialization of W_s , the W_x can be updated by differentiating Eq. 14 with respect to W_x and setting it to zeros. Here we directly give the analytical solution as follows:

$$W_x = (K_x(\hat{B}_x + 2\lambda_1 L_x + 2\lambda_2 I)K_x^\top)^{-1} K_x Q K_s^\top W_s, \quad (15)$$

where $Q(i, j) = \mathbf{1}(i, j)$. With the updated W_x in hand, a new W_s is able to be obtained in a similar way, namely setting the partial differential of Eq. 14 with respect to W_s to zeros. The W_s is updated as

$$W_s = (K_s(\hat{B}_s + 2\lambda_1 L_s + 2\lambda_2 I)K_s^\top)^{-1} K_s Q K_x^\top W_x. \quad (16)$$

D. Tracking with the learned distance metric

In the above section, we have learned the mapping functions using the samples extracted from the first frame of a test image sequence to project points from Euclidean space and Riemannian manifold Sym_D^+ into a common subspace. Based on these mapping functions, when a new frame comes, we perform the following steps to determine the new position and scale of the target:

Step 1: In the t -th frame sampling target candidates $y_1, \dots, y_q$ under the Gaussian distribution $\mathbf{G}_p(\mu_p, \sigma_p)$, where

$$\begin{aligned} \mu_p &= (p_x^{t-1}, p_y^{t-1}), \\ \sigma_p &= 1, \end{aligned} \quad (17)$$

and (p_x^{t-1}, p_y^{t-1}) is the target position in the $(t-1)$ -th frame. The sampling scales N_s subject to

$$N_s = N_o \times 1.05^{\max(-1, \min(1, 5 \times \text{Gaussian}(0, 1)))}, \quad (18)$$

Algorithm 1: Visual Tracking based on Point-to-Set DML

- 1 **Initialization:** Randomly sampled target and background training templates from the starting frame.
 - 2 Divide the training templates into target template sets and background template sets using the K-means method according to Eq. (3);
 - 3 Optimize the point-to-set distance metric Eq. (5) by alternatively updating W_x Eq. (15) and W_s Eq. (16);
 - 4 **for** $t = 2, 3, \dots$ **do**
 - 5 Sample target candidates $y_1, \dots, y_q$ according to Gaussian distribution Eq. (17) and Eq. (18);
 - 6 Project to the common subspace using the learned mapping matrix W_x and W_s according to Eq. (19);
 - 7 Compute the distance between target candidates to target template sets using Eq. (21);
 - 8 The final target state is the average of the top 5 minimal distance candidates;
 - 9 **end**
-

where N_o denotes the scale of the target in the last frame. Then, features of these candidates are computed as doing in the first frame. For simplicity, these features are still denoted by $Y = y_1, \dots, y_q$.

Step 2: Mapping target candidates, target template sets, and background sets to the common subspace,

$$\begin{aligned} \hat{Y} &= W_x^\top K_y = W_x^\top [\hat{K}_y, \hat{K}_{y,s}], \\ \hat{S} &= W_s^\top K_s = W_s^\top [\hat{K}_s, \hat{K}_{y,s}^\top], \end{aligned} \quad (19)$$

where

$$\begin{aligned} \hat{K}_y(i, j) &= \exp(-\|y_i - y_j\|^2 / (2\sigma^2)), \\ \hat{K}_s(i, j) &= \exp(-\|\log(S_i) - \log(S_j)\|^2 / (2\sigma^2)) \\ \hat{K}_{y,s}(i, j) &= \exp(-(y_i - e_j)^\top S_j^{-1} (y_i - e_j) / (2\sigma^2)). \end{aligned} \quad (20)$$

Step 3: In the common subspace computing the distance between target candidates and target template sets $\hat{S}_1^+, \dots, \hat{S}_{m_k}^+$ according to Eq. 21, where $\hat{S}_i^+$ is the counterpart of S_i^+ in $\hat{S}$.

$$d(y_i, S^+) = \sum_{j=1}^{m_k} d(y_i, S_j^+) = \sum_{j=1}^{m_k} (1 - \frac{\hat{Y}_i^\top \hat{S}_j^+}{\|\hat{Y}_i\|_2 \|\hat{S}_j^+\|_2}). \quad (21)$$

Step 4: The final target state is the average of the top 5 minimal distance candidates. We summarize the main steps of the proposed tracking algorithm in Alg. 1.

IV. EXPERIMENTS

In this section, we first describe the implementation details and then quantitatively and qualitatively evaluate the proposed Point-to-Set distance metric learning based Tracker (PST) on 31 publicly used challenging sequences. These videos are full of challenges such as heavy illumination variations, partial or

TABLE I
COMPARISON OVER THE AVERAGE OVERLAP RATE (THE LARGER THE BETTER). THE BEST AND THE SECOND BEST RESULTS ARE SHOWN IN RED AND BLUE COLORS, RESPECTIVELY.

	PST	Struck	SCM	IVT	L1APG	MTT	CXT	Frag	TLD	DLT	ASLA	DFT	LOT	LSST	MEEM	DSST	DAT	PPT
Boy	0.821	0.760	0.377	0.260	0.734	0.500	0.542	0.389	0.662	0.828	0.369	0.401	0.533	0.358	0.797	0.138	0.680	0.805
Suv	0.563	0.519	0.750	0.406	0.476	0.449	0.736	0.628	0.693	0.787	0.495	0.079	0.654	0.611	0.627	0.148	0.098	0.540
Tiger1	0.597	0.153	0.157	0.095	0.314	0.260	0.322	0.265	0.376	0.372	0.290	0.532	0.139	0.094	0.649	0.213	0.415	0.586
Tiger2	0.525	0.544	0.090	0.086	0.244	0.287	0.359	0.118	0.262	0.214	0.145	0.681	0.135	0.088	0.540	0.149	0.448	0.556
Walking	0.604	0.572	0.711	0.766	0.753	0.666	0.171	0.537	0.446	0.413	0.772	0.562	0.704	0.757	0.540	0.159	0.547	0.701
CarDark	0.595	0.892	0.843	0.663	0.884	0.827	0.566	0.301	0.449	0.588	0.849	0.380	0.420	0.835	0.862	0.177	0.031	0.533
Deer	0.725	0.740	0.071	0.033	0.602	0.612	0.697	0.173	0.602	0.041	0.033	0.256	0.198	0.033	0.745	0.148	0.118	0.709
Dudek	0.846	0.730	0.769	0.753	0.692	0.758	0.731	0.535	0.648	0.791	0.737	0.690	0.536	0.796	0.715	0.142	0.170	0.851
FaceOcc2	0.653	0.785	0.728	0.727	0.687	0.745	0.742	0.648	0.616	0.654	0.646	0.768	0.458	0.463	0.765	0.130	0.273	0.659
Football1	0.592	0.669	0.396	0.557	0.557	0.556	0.763	0.364	0.377	0.343	0.493	0.867	0.536	0.480	0.680	0.352	0.661	0.686
Girl	0.716	0.746	0.682	0.167	0.730	0.665	0.554	0.454	0.572	0.543	0.711	0.283	0.418	0.151	0.698	0.249	0.460	0.704
Jogging-1	0.621	0.171	0.178	0.176	0.174	0.177	0.766	0.518	0.770	0.181	0.179	0.187	0.092	0.175	0.670	0.036	0.177	0.754
Jumping	0.596	0.617	0.122	0.122	0.150	0.097	0.524	0.672	0.664	0.580	0.227	0.110	0.578	0.126	0.708	0.010	0.048	0.649
Liquor	0.561	0.412	0.319	0.226	0.199	0.207	0.257	0.330	0.518	0.348	0.247	0.222	0.828	0.207	0.789	0.161	0.335	0.555
Matrix	0.452	0.098	0.255	0.024	0.147	0.233	0.058	0.057	0.156	0.012	0.121	0.058	0.111	0.083	0.394	0.051	0.068	0.306
Mhyang	0.757	0.818	0.809	0.796	0.829	0.853	0.850	0.651	0.632	0.887	0.916	0.709	0.215	0.834	0.790	0.167	0.591	0.810
MotorRolling	0.461	0.154	0.111	0.089	0.093	0.090	0.129	0.118	0.229	0.091	0.106	0.084	0.121	0.098	0.110	0.029	0.091	0.576
Singer1	0.519	0.358	0.868	0.574	0.285	0.340	0.492	0.205	0.725	0.854	0.792	0.355	0.194	0.877	0.327	0.124	0.335	0.788
BlurCar4	0.754	0.846	0.411	0.145	0.867	0.780	0.764	0.560	0.717	0.685	0.380	0.717	0.561	0.528	0.795	0.153	0.807	0.398
Human3	0.584	0.007	0.006	0.007	0.006	0.006	0.011	0.015	0.006	0.007	0.007	0.007	0.011	0.007	0.527	0.004	0.065	0.045
Board	0.749	0.652	0.575	0.191	0.132	0.198	0.291	0.512	0.091	0.538	0.309	0.325	0.209	0.236	0.612	0.122	0.044	0.752
Car24	0.487	0.139	0.862	0.663	0.776	0.854	0.787	0.115	0.568	0.769	0.783	0.077	0.290	0.857	0.433	0.236	0.357	0.643
Dog	0.521	0.344	0.391	0.131	0.396	0.383	0.645	0.334	0.590	0.471	0.518	0.311	0.453	0.097	0.355	0.108	0.356	0.494
KiteSurf	0.567	0.640	0.267	0.287	0.248	0.298	0.323	0.126	0.337	0.210	0.245	0.389	0.029	0.316	0.685	0.063	0.242	0.698
Man	0.775	0.898	0.828	0.750	0.852	0.882	0.850	0.201	0.739	0.796	0.850	0.202	0.185	0.803	0.831	0.176	0.506	0.802
Panda	0.570	0.517	0.492	0.106	0.262	0.163	0.185	0.329	0.397	0.462	0.502	0.279	0.041	0.224	0.487	0.067	0.556	0.555
RedTeam	0.631	0.497	0.482	0.629	0.570	0.538	0.380	0.138	0.354	0.698	0.617	0.272	0.100	0.407	0.511	0.162	0.459	0.635
Skater	0.559	0.632	0.519	0.552	0.605	0.628	0.623	0.509	0.434	0.578	0.564	0.359	0.445	0.533	0.572	0.145	0.568	0.556
Skating2-2	0.464	0.385	0.400	0.094	0.039	0.061	0.058	0.207	0.046	0.134	0.282	0.052	0.366	0.076	0.378	0.046	0.137	0.489
Surfer	0.707	0.369	0.395	0.069	0.040	0.101	0.731	0.222	0.674	0.397	0.403	0.042	0.323	0.129	0.496	0.070	0.437	0.745
Twinnings	0.705	0.579	0.520	0.414	0.582	0.441	0.436	0.471	0.352	0.657	0.555	0.485	0.504	0.691	0.567	0.139	0.487	0.583
Average	0.622	0.524	0.464	0.341	0.449	0.440	0.495	0.345	0.474	0.482	0.456	0.347	0.335	0.386	0.602	0.131	0.341	0.618

full occlusions, abrupt camera shaking, large scale changes, in plane or out-of-plane rotation, large object deformation, and heavy motion blur, to name a few.

The proposed trackers are compared to 16 state-of-the-art trackers: correlation filter based tracker with scale estimation (DSST) [51], distractor-aware tracker (DAT) [52], multi-expert based tracker (MEEM) [19], structured output tracking (Struck) [18], holistic and local sparsity based tracker (SCM) [16], tracking-learning-detection tracker (TLD) [53], adaptive local sparse appearance model based tracker (ASLA) [54], multi-task sparse learning based tracker (MTT) [55], deep learning based tracker (DLT) [56], context tracker (CXT) [57], fragments based tracker (Frag) [58], incremental learning based tracker (IVT) [59], ℓ_1 sparse tracker using APG (L1APG) [60], distribution fields for tracking (DFT) [61], locally orderless tracking (LOT) [62], and least soft-threshold squares tracking (LSST) [63]. In addition, we make a comparison to an ITML [64] based tracker, denoted as PPT. ITML is employed to learn a distance metric in the case, which uses the cluster center to replace the image set in each training pair.

The average success rate and average center location error are employed to measure the performance in the quantitative evaluations following the recently developed algorithms [16], [54], [56], [65]. The average success rate is defined as $\frac{1}{N} \sum_{i=1}^N \frac{|B_i^t \cap B_i^{gt}|}{|B_i^t \cup B_i^{gt}|}$, where B_i^t is the tracked result at the i th frame by the tracker in the format of a rectangle bounding box, B_i^{gt} is the ground truth at the i th frame, N is the total number of frames in the test image sequence. The average center location error is the average Euclidean distance in pixels between center points of the tracked bounding box and the

ground truth.

A. Implementation details

To start the proposed tracker, $m = 500$ positive examples and $n = 5000$ negative examples are sampled in the first frame to learn the mapping functions. These examples are all resized to 107×107 pixels. Each example is represented by a 512-dimensional vector extracted by the output of the FC6 layer of the convolutional neural network MDNet [10]. Then, we cluster these examples into $m_k = 7$ target template sets and $n_k = 20$ background template sets using the standard K-means method. The values of m_k and n_k are determined to seek a balance between the computation cost and the tracking accuracy. The trade-off parameters λ_1, λ_2 , and λ_3 are set to 1, 0.01, and 0.1, respectively, which are determined by grid search in a wide range as shown in Table II. The neighborhood number k_1 and k_2 are both set to 1. When optimizing the objective, we find that the alternative iteration number 30 can lead to a desirable solution.

B. Quantitative evaluation

Table I shows the performance comparison on 31 challenging image sequences in terms of the average overlap rate. From Table I we can observe that the proposed PST ranks top two on most of the sequences, which demonstrates its favourable performance compared to other state-of-the-art trackers. In particular, our tracker achieves an improvement of more than 20 percent over the second best one on the *MotorRolling* sequences, where the tracking target undergoes the combination of heavily rotations, illumination changes,

Fig. 3. Frame-by-frame center location errors of our tracker PST against other six state-of-the-art trackers on several challenging image sequences.

Fig. 4. Bounding boxes of our tracker PST against other six state-of-the-art trackers on challenging image sequences.

TABLE II
TRACKING PERFORMANCE IN TERMS OF AVERAGE BOUNDING BOX OVERLAP OBTAINED BY VARYING THE KEY PARAMETERS λ_1 , λ_2 , AND λ_3 IN A LARGE RANGE.

	$\lambda_1 = 0.01$			$\lambda_1 = 0.1$			$\lambda_1 = 1$		
	$\lambda_3 = 0.01$	$\lambda_3 = 0.1$	$\lambda_3 = 1$	$\lambda_3 = 0.01$	$\lambda_3 = 0.1$	$\lambda_3 = 1$	$\lambda_3 = 0.01$	$\lambda_3 = 0.1$	$\lambda_3 = 1$
$\lambda_2 = 1$	0.416	0.269	0.221	0.375	0.275	0.059	0.404	0.311	0.123
$\lambda_2 = 0.1$	0.247	0.116	0.419	0.305	0.151	0.422	0.361	0.142	0.470
$\lambda_2 = 0.01$	0.186	0.492	0.364	0.149	0.457	0.435	0.144	0.622	0.493

TABLE III
COMPARISON OVER THE AVERAGE CENTER LOCATION ERROR IN PIXELS (THE SMALLER THE BETTER). THE BEST AND THE SECOND BEST RESULTS ARE SHOWN IN RED AND BLUE COLORS, RESPECTIVELY.

	PST	Struck	SCM	IVT	LIAPG	MTT	CXT	Frag	TLD	DLT	ASLA	DFT	LOT	LSST	MEEM	DSST	DAT	PPT
Boy	1.9	3.8	51.0	91.3	7.0	12.8	7.4	40.5	4.5	2.3	106.1	106.3	66.0	109.3	2.5	28.4	6.1	2.1
Suv	63.7	49.8	4.6	57.3	93.1	180.7	9.9	42.0	13.0	4.4	74.8	111.4	29.5	33.4	29.8	51.8	110.1	48.4
Tiger1	19.2	128.7	93.5	106.6	58.4	64.4	45.4	74.3	49.5	37.2	55.9	41.3	111.4	111.8	13.7	48.8	31.6	19.7
Tiger2	24.6	21.6	141.2	105.1	65.2	48.8	41.4	113.5	37.1	48.5	85.8	12.2	150.4	81.1	19.5	61.5	30.0	20.0
Walking	4.0	4.6	2.5	1.6	3.3	3.5	205.7	9.3	10.2	15.4	1.9	5.9	2.4	1.6	4.8	30.3	6.9	3.4
CarDark	7.9	1.0	1.2	8.4	1.0	1.6	16.5	36.5	27.5	18.8	1.5	58.8	30.9	1.4	1.3	17.2	104.7	10.6
Deer	6.2	5.3	103.5	182.7	24.2	18.9	6.7	105.1	30.9	236.7	160.1	98.7	65.2	232.7	4.7	53.8	143.9	5.9
Dudek	8.6	11.4	10.8	9.6	23.5	14.1	12.8	82.7	18.1	8.8	15.3	18.7	85.1	9.1	14.6	117.0	199.5	8.0
FaceOcc2	12.1	6.0	9.0	7.4	12.8	9.8	6.3	16.0	12.3	10.9	19.3	7.9	14.9	10.6	6.8	60.4	46.7	18.0
Football1	9.8	5.4	20.3	24.5	9.2	12.7	2.6	15.7	45.4	25.7	12.2	2.0	6.8	11.5	5.1	15.9	5.4	8.8
Girl	3.3	2.6	2.5	22.5	2.8	4.3	11.0	20.7	9.8	10.1	3.3	24.0	22.8	26.7	3.6	16.2	15.2	6.6
Jogging-1	15.6	62.1	132.8	86.1	89.5	108.0	5.6	21.5	6.7	108.0	104.6	31.4	90.9	95.5	6.2	107.3	92.8	7.5
Jumping	5.3	6.5	65.9	61.6	83.7	84.6	10.0	5.6	5.9	8.7	46.1	67.1	5.6	60.4	4.4	78.3	50.7	5.6
Liquor	59.4	91.0	99.2	118.5	212.9	543.4	131.8	99.6	37.6	113.2	146.7	221.1	8.5	166.7	11.3	126.4	171.9	58.7
Matrix	31.7	194.5	48.2	124.4	61.7	75.4	151.6	181.5	57.2	184.0	65.2	105.8	73.5	111.4	60.5	61.2	107.5	49.2
Mhyang	1.9	2.6	2.4	1.9	3.2	3.1	4.0	12.5	9.5	2.4	1.7	9.1	113.1	2.1	4.5	44.8	14.8	1.6
MotorRolling	45.6	145.7	177.6	174.7	207.0	191.1	131.8	146.2	80.9	193.0	201.4	174.2	135.4	144.9	163.7	286.5	145.1	17.2
Singer1	26.8	14.5	2.7	11.3	53.4	36.2	11.4	88.9	8.0	3.0	3.3	18.8	141.4	2.8	29.7	85.1	35.5	3.4
BlurCar4	8.9	4.9	63.6	133.7	6.6	13.6	8.8	56.8	20.1	27.2	71.5	18.5	26.9	44.5	10.8	102.9	10.5	118.9
Human3	16.6	230.6	521.1	227.9	283.9	428.6	164.9	224.2	249.4	232.4	249.4	227.1	226.6	245.4	13.6	348.3	188.8	196.1
Board	17.9	33.6	44.5	150.2	173.2	147.6	126.0	91.4	248.4	52.1	100.9	99.3	182.0	84.7	44.4	156.0	319.8	18.0
Car24	73.0	119.7	1.9	1.4	2.1	2.6	3.5	127.1	3.0	1.9	3.0	165.6	100.0	2.2	4.9	17.6	12.1	12.0
Dog	6.0	10.4	11.1	93.4	9.2	6.1	4.6	12.2	6.1	9.3	5.3	15.8	10.3	38.0	7.2	28.6	7.3	5.8
KiteSurf	4.8	6.1	66.2	53.8	43.5	54.7	36.8	141.1	58.6	37.3	25.9	32.4	84.4	45.5	3.3	45.8	59.0	3.3
Man	2.7	1.4	1.9	2.9	1.3	1.5	2.2	57.0	3.4	1.4	1.5	39.9	33.1	1.9	2.3	21.1	9.7	2.2
Panda	5.2	7.2	7.2	79.8	50.9	20.2	64.0	61.7	32.1	7.0	7.4	48.5	78.3	31.7	7.4	43.6	6.0	5.1
RedTeam	3.4	4.3	4.1	3.3	4.0	2.7	16.8	54.9	35.5	3.0	3.3	50.3	71.9	45.0	3.5	19.3	4.9	3.5
Skater	10.3	8.2	13.2	8.7	14.5	7.8	7.6	24.3	12.8	10.2	7.8	46.0	9.5	11.7	11.8	81.0	16.6	9.7
Skating2-2	33.7	75.4	51.4	198.2	198.5	196.7	213.2	126.8	299.5	189.9	90.7	236.7	51.0	203.3	42.2	234.5	171.3	31.4
Surfer	3.7	9.0	14.8	63.5	101.4	37.0	3.1	51.6	3.8	24.0	22.9	150.9	26.1	23.4	7.0	50.6	7.1	3.2
Twinnings	5.5	5.5	16.9	13.8	8.1	15.0	21.3	16.9	15.6	6.8	11.5	12.4	20.5	5.7	7.9	37.2	16.5	16.0
Average	17.4	41.1	57.6	71.8	61.6	75.7	47.9	69.6	46.9	52.7	55.0	72.8	66.9	64.4	17.8	79.9	69.3	23.2

TABLE IV
COMPARISON OF RUNNING SPEED (THE LARGER THE BETTER). THE BEST AND THE SECOND BEST RESULTS ARE SHOWN IN RED AND BLUE COLORS, RESPECTIVELY.

	PST	Struck	SCM	IVT	LIAPG	MTT	CXT	Frag	TLD	DLT	ASLA	DFT	LOT	LSST	MEEM	DSST	DAT	PPT
FPS	0.17	10.14	0.36	27.24	1.94	0.79	13.67	4.60	20.66	8.68	7.55	11.05	0.48	4.33	21.32	53.48	82.43	1.64

and deformations. On the most challenging sequence *Matrix*, where the appearance of the tracking target is severely interfered by thick darkness, thunder, and heavy rain, the majority of the compared trackers achieves an average overlap rate lower than 0.1. In contrast, our tracker attains up to 0.45, which is 6 percent higher than the second best.

Table III presents the average center location error comparisons, where a smaller value means better performance. It can be seen that the proposed PST method is able to track targets with a relatively smaller spatial errors on most of the sequences. Taking the *Board* image sequence for example, the target undergoes complicated challenges including scale variations, out-of-view, motion blur, and out-of-plane rotation of 360°, which makes tracking the target a very tough task. Our tracker achieves the minimal average center location error with 17.9 pixels, which is 15.7-pixel smaller than the second best one. In such a challenging scenario, with the leading

average overlap rate in Table I on the *Matrix* image sequence, our tracking result here is also 25.5-pixel more precise than the second best. Overall, from Table III and Table I we can see that our tracker performs favorably against other state-of-the-art methods in terms of both criteria.

To make a more comprehensive evaluation of the proposed tracker, in Figure 3 we show the detailed frame-by-frame center location errors of our tracker compared to other state-of-the-art trackers on several challenging image sequences. From these plots we can see that the proposed PST can achieve consistent lower center location errors than the other trackers, which demonstrates the robustness and the effectiveness of our tracker. The effectiveness of the proposed tracking algorithm can be attributed to two aspects: (1) Given a specific task, the specially learned distance metric for this task is usually better than the Euclidean distance. (2) The adopted deep convolutional features generally are more discriminative than

traditional hand-crafted features.

Table IV presents the run-time of evaluated tracking methods. The results show that DAT and DSST run very fast with FPS larger than 50, and the proposed tracking method runs at 0.17 FPS. Taking also the tracking accuracy into consideration, although our PST runs slow, it achieves a more than 30% higher performance than the fastest trackers DAT and DSST in terms of the average overlap rate as shown by the last row of Table I and more than 50 pixels preciser in terms of the average center local error metric as shown by the last row of Table III. Compared to other trackers running at a similar speed such as SCM, MTT, and LOT, the proposed tracking method PST also has at least a 10% improvement as shown by Table I and III.

C. Qualitative evaluation

In addition to the quantitative evaluation, we also evaluate the proposed algorithm qualitatively against other state-of-the-art trackers on several challenging sequences. We present the qualitative bounding box comparisons in Figure 4.

1) *Out-of-plane Rotation*: The target in the *Girl* image sequence poses a tough tracking task that contains a 360° out-of-plane rotation, which shows the front face, the side face, the back side of the head, and the other side face in turn. As shown in Figure 4 (g), our PST method is able to locate the target precisely even when the side face and the back of the head appear as shown in frames 171, 236, and 245, although our training examples are sampled only from the first frame and keep unchanged throughout the whole sequences. This can be attributed to the learned point-to-set distance metric, which exploits all the training samples in the target template set and the background template set to measure the distance to a target candidate. While there are no new target templates added to the training sets, the existing background templates including blue windows, yellow wooden wall, and white T-shirt can be used to push candidates with background regions away by the learned point-to-set distance metric, which shows the advantage of exploiting the rich features of all the training samples rather than the fixed support vectors in SVMs. In contrast, other state-of-the-art trackers, such as MEEM, DSST, and ASLA, encounter drifts to some extent.

2) *Occlusion, Scale Variation, and Deformation*: As shown in Figure 4 (e), the target of the *Dudek* image sequence undergoes significant occlusions (more than half of the face is occluded by his hand, see frame 211), scale variation, and deformations (such as facial expression changes and with/without eyeglasses). We can observe that the proposed PST method achieves very good results in these cases, as shown in frames 211, 906, 1073, and 1145. This can be attributed to the learned point-to-set distance metric. Specifically, taking the occluded frame 211 for example, although the occluded face with a hand does not appear in the target template sets, it neither appears in the background templates set. Thus, candidates with occluded face are still able to obtain a relatively large distance to the background set compared to candidates that have an overlap with the background. As a result, the occluded target can be distinguished from backgrounds. Except the TLD

tracker, the remaining trackers also perform very well in the presence of occlusions.

3) *Severe Blur and Cluttered Background*: As shown in frame 294 and frame 239 of Figure 4 (a) and (h) respectively, the targets in sequences *BlurCar4* and *Jumping* are severely blurred in the cluttered background due to either abrupt fast motion of the camera or the fast motion of the target itself. From the results we can see that our tracker can handle these challenges well. In contrast, other state-of-the-art trackers, such as SCM and DSST, fail to locate the target after heavy blur occurs.

V. CONCLUSION

This paper presents a novel tracking algorithm based on the point-to-set distance metric learning for object tracking in autonomous driving applications. The point-to-set distance metric was learned by minimizing the intra-class distance and meanwhile maximizing the inter-class distance in the common subspace after a two-step projection. With the learned distance metric, we are able to measure each target candidate with the reference to all the training samples instead of some fixed support vectors in SVMs. Numerous experimental results on challenging image sequences demonstrate the effectiveness of the proposed method compared to other state-of-the-art trackers.

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