Cluster-based Dictionary Learning and Locality-constrained Sparse Reconstruction for Trajectory Classification

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Outline

1. Introduction

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Motivation

- Visual trajectory classification contributes to a variety of applications, including the identification of crowdedness, behaviors, activities and events of video scenes.

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- Visual trajectory classification contributes to a variety of applications, including the identification of crowdedness, behaviors, activities and events of video scenes.
- Although extensively investigated, the limited sizes of labeled sample sets, and the local variation and noises of the trajectories are still an open research problems.

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- To solve the problems in trajectory classification about automatically modeling unlabeled and incomplete trajectories.
- Cluster-based dictionary learning (CDL) and locality-constrained sparse reconstruction (LSR) are proposed.
- Experimental results show that our approach outperforms several recent approaches.

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1. Introduction
2. Overview of the framework

Overview of the framework

- Two stages: Learning & Classifying

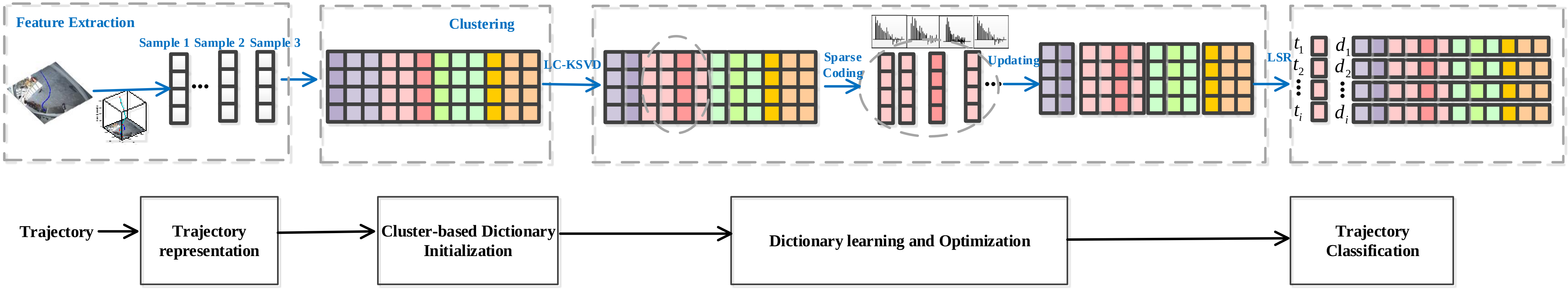

Fig.1. Overview of the proposed approach.

- ✓ Given a video scenario, we firstly assign trajectories into clusters based on the representative vectors.
- ✓ In the learning stage, an initial dictionary is obtained with the clustered trajectories and their corresponding labels. Then, a label consistency constraint and optimal criteria are incorporated to learn the dictionary.
- ✓ In the classifying stage, a multiple-category classifier for trajectory is used to estimate trajectory label based on the LSR with learned dictionary.

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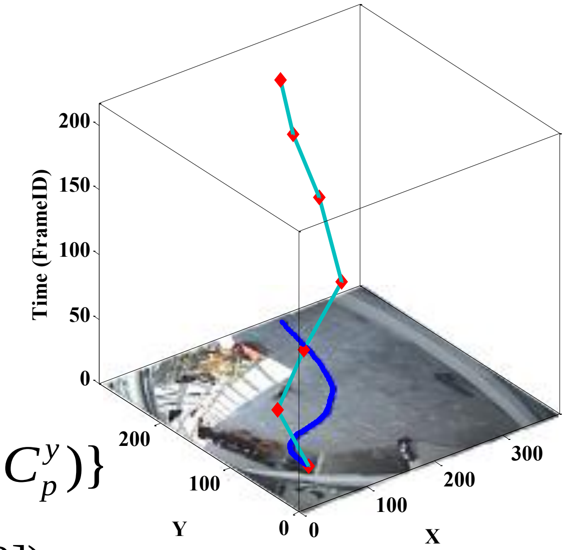
3. Cluster-based dictionary learning

Cluster-based dictionary learning

Trajectory representation



- Given a trajectory $t_i = \{(P_1^x, P_1^y), \cdots, (P_n^x, P_n^y)\}$
  - n — length of trajectory
  - (P_n^x, P_n^y) — n-th position point of the trajectory
- Control point-based feature representation $y_i = \{(C_1^x, C_1^y), \cdots, (C_p^x, C_p^y)\}$
  - (C_p^x, C_p^y)— the p-th control point on B-spline basis function (predefined in [19])
  - p — number of control points
  - C_p^y、C_p^x— the normalized x-coordinate and y-coordinate
- LCSCA feature vector

[19] C. Li, Z. Han, Q. Ye, J. Jiao, "Visual abnormal behavior detection based on trajectory sparse reconstruction analysis," Neurocomputing, vol. 119, pp. 94-100, 2013.

Cluster-based dictionary learning

Cluster-based dictionary initialization

- firstly apply the K-means clustering with DTW distance
- given *N* trajectories as $T = [t_1, \cdots, t_N] \in \mathbb{R}^{n \times N}$
  - y_i — LCSCA feature vector of trajectory t_i
- a set of *N* feature vectors as $Y = [y_1, \cdots, y_N] \in \mathbb{R}^{p \times N}$
  - learning a reconstructive dictionary D with M items for sparse representation of Y

    $$\langle D, X \rangle = \underset{D,X}{\operatorname{argmin}} \|Y - DX\|_2^2, \quad s.t. \forall i, \|x_i\|_0 \le \varepsilon$$
  - $D^{(0)}$— the initial dictionary $D^{(0)} = \left[C^{(1)}, \cdots, C^{(k)}, \cdots C^{(K)}\right]$
  - $C^{(k)}$— the clustering results $C^{(k)} = \left[y_1^{(1)}, \cdots, y_{N_k}^{(k)}\right]$
  - x_i — the sparse representation of y_i on D

Cluster-based dictionary learning

Dictionary learning and optimization

(1) keeping D fixed to find X-sparse coding

(2) keeping X fixed to find D–SVD decompositions

$$Y_{new} = \left(Y^T \quad \sqrt{\alpha} Q^T \quad \sqrt{\beta} H^T \right)^T$$

$$D_{new} = \left(D^T \quad \sqrt{\alpha} A^T \quad \sqrt{\beta} W^T \right)^T$$

- LC-KSVD algorithm [21] to solve the objective function: $\langle D, W, A, X \rangle = \underset{D,W,A,X}{\operatorname{argmin}} \| Y_{new} - D_{new} X \|_2^2 \quad s.t. \forall i, \|x_i\|_0 \le \varepsilon$
- A、W — discriminative sparse code error、classification error
- α、β — to control the relative contribution between reconstruction and label consistence regularization
- incremental updating the D and X as training vectors come
- the set of labels is also updated according to clustering

[21] Z. Jiang, Z. Lin, and L.S. Davis, “Label consistent k-svd: learning a discriminative dictionary for recognition,” TPAMI, vol. 35, no. 11, pp. 2651-2664, 2013.

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4. Locality-constrained sparse reconstruction (Classifying)

Locality-constrained sparse reconstruction

Partition

- partition the trajectories into tracklets (trajectory segments)
- align the tracklets to construct a local dictionary in [16]

$$D=\left[d_1 \quad \cdots \quad d_i \quad \cdots \quad d_{p-1}\right]^T,\ i=1,\dots,p-1$$

- i-th tracklets of J kinds trajectories

$$d_i=\{a_1^1(i),a_1^2(i),\dots,a_1^K(i),\dots,a_J^K(i)\}$$

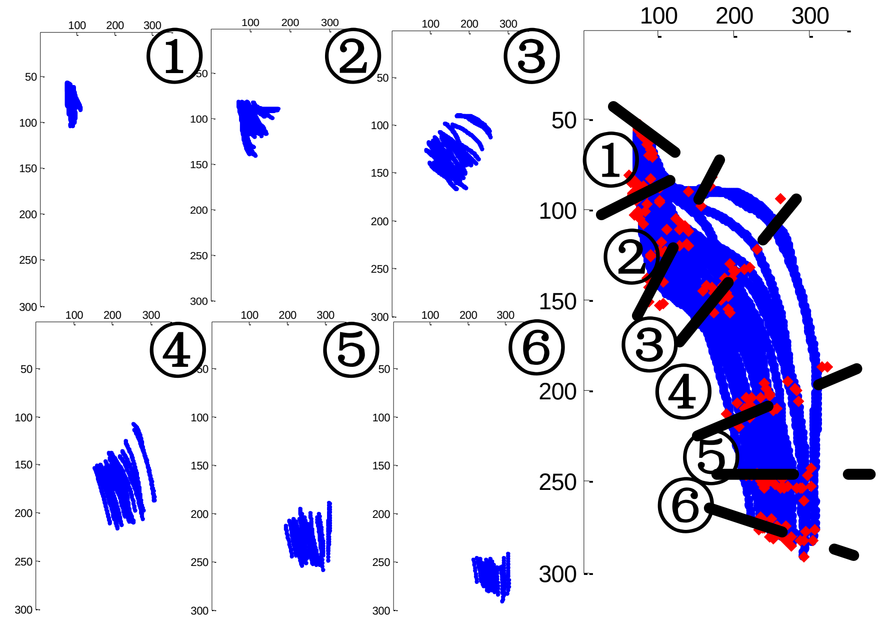

Fig.2. Examples of a class of similar trajectories and their partitioned tracklets. Left: six partitioned tracklets from a class of similar trajectories (blue curves). Right: the whole trajectories with control points (red dots).

[16] C. Li, Z. Han, S. Gao, L. Pang, Q. Ye, and J. Jiao, "Locality-constrained Sparse Reconstruction for Trajectory Classification," in ICPR, 2014, pp. 2602-2606.

Locality-constrained sparse reconstruction

Classification

- sparse linear reconstruction with locality-constrained dictionary $t_i \approx d_i \psi_i$
  - trajectory is represented as the combination of the feature vectors of some tracklets
  - each tracklet is approximately represented as a linear superposition of the local dictionary
- discriminate encoding and loss weighted decoding strategy
  - combination of reconstruction results from multiple tracklets
  - discriminate encoding *M*: M_{ij} — assign the *i*-th tracklet to the *j*-th class
  - loss-based decoding — to classify a trajectory by assigning a label with minimal decoding measure (detailed in [16])

[16] C. Li, Z. Han, S. Gao, L. Pang, Q. Ye, and J. Jiao, "Locality-constrained Sparse Reconstruction for Trajectory Classification," in ICPR, 2014, pp. 2602-2606.

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5. Experimental results

Experimental results

Datasets

- CAVIAR [27]
  - contains a series of trajectories in an entrance lobby with 11 entry-exit routes
  - 1100 trajectories in the training set and 1121 trajectories in the testing set
- Carpark [28]
  - contains 269 trajectories with 8 categories of trajectories in three crossroads
  - 124 training trajectories and 145 testing trajectories

[27] CAVIAR: http://homepages.inf.ed.ac.uk/rbf/CAVIAR

[28] H.M. Dee, and D. Hogg, "Detecting inexplicable behavior," in BMVC, 2004, pp.1-10.

Experimental results

Algorithms compared

- HKM (Hierarchical K-Means) [13]
- PSC (Parallel Spectral Cluster) [29]
- GMMs (Guassian Mixture Models) [5]

Experimental setting

- α、β are respectively set to 0.01 and 1 to learn the dictionary with 110 items (M=110). We evaluate the classification ability of our approach compared with three methods using 5, 15, 25, 35, 45, and 50 training samples per category, respectively.

Experimental results

Table 1. Comparisons of classification accuracy (%) in the CAVIAR dataset.

Method	Number of training samples per class					
	5	15	25	35	45	50
HKM [13]	19.8	28.4	35.9	36.7	38.9	45.9
PSC [29]	21.9	23.6	37.1	38.6	47.4	68.3
GMMs [5]	-	-	-	-	-	38.6
Our approach	**38.7**	**58.4**	**65.5**	**67.3**	**70.1**	**72.3**

Table 2. Comparisons of classification accuracy (%) in the Carpark dataset.

Method	Number of training samples per class		
	5	10	15
HKM [13]	17.9	33.7	37.5
PSC [29]	18.5	36.9	45.8
GMMs [5]	-	-	38.4
Our approach	38.1	66.7	69.2

Experimental results

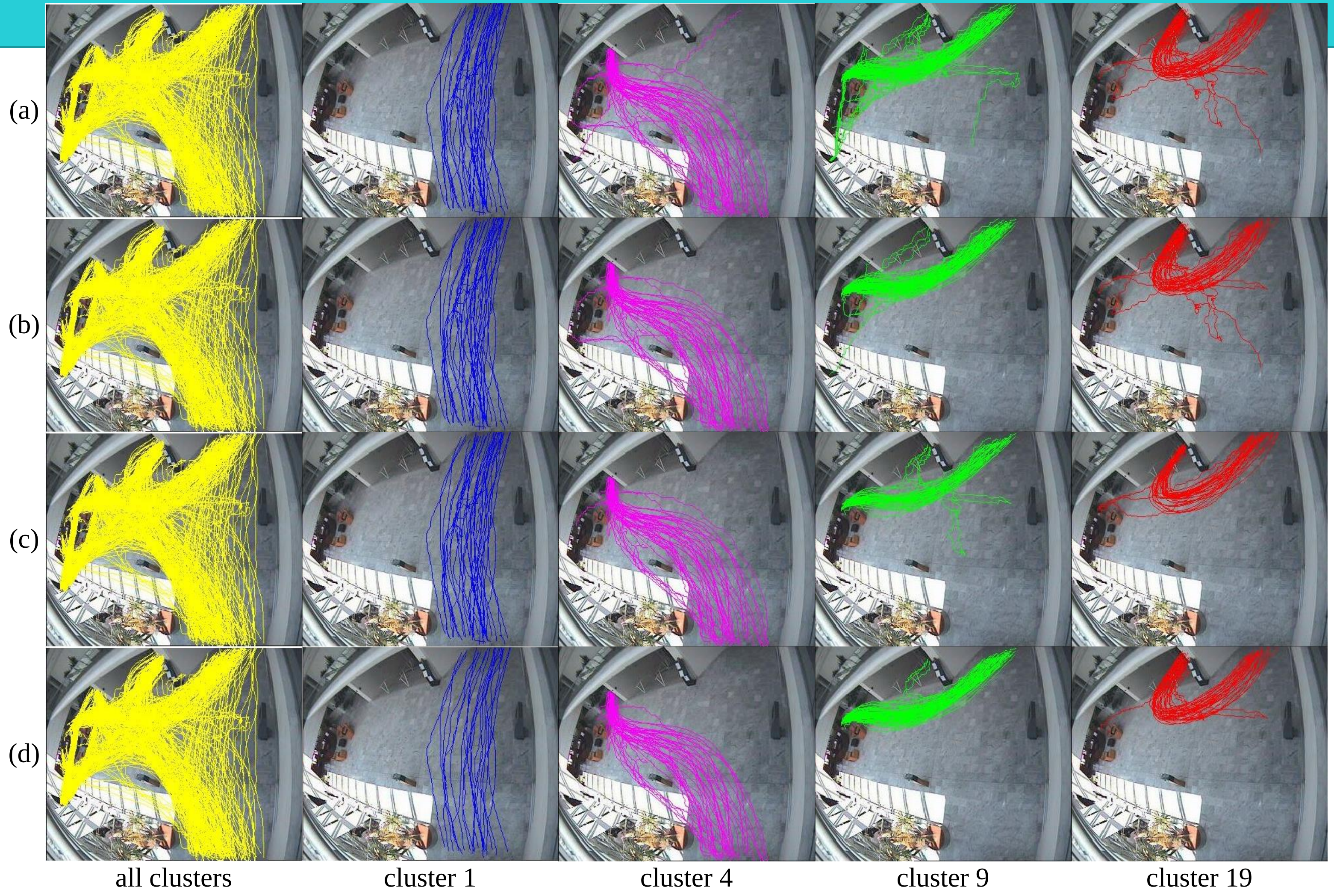

Fig.3. Examples of classified testing trajectories in the CAVIAR dataset. The results of: (a) HKM, (b) PSC, (c) GMMs, (d) our proposed approach.

Experimental results

(a)

(b)

(c)

(d)

all clusters | cluster 1 | cluster 3 | cluster 6 | cluster 7

Fig.3. Examples of classified testing trajectories in the CAVIAR dataset. The results of: (a) HKM, (b) PSC, (c) GMMs, (d) our proposed approach.

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Conclusion

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- By introducing label consistency constraint and label updating strategy in the dictionary, the incremental CDL approach can learn the dictionary that explores the importance of the label consistency constraint and classification optimization.
- On the learned dictionary, we obtain a multiple-category classifier based on LSR that explores both sparsity and local adaptability for robust trajectory classification.

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- By introducing label consistency constraint and label updating strategy in the dictionary, the incremental CDL approach can learn the dictionary that explores the importance of the label consistency constraint and classification optimization.
- On the learned dictionary, we obtain a multiple-category classifier based on LSR that explores both sparsity and local adaptability for robust trajectory classification.
- Experimental results on two public datasets show the good performance of our approach.
- Future work includes exploring better optimization algorithms to train the automatic parameter setting.

Thank you！ Any Questions？

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