CPS: SYNERGY: DISTRIBUTED SENSING, LEARNING AND CONTROL IN DYNAMIC ENVIRONMENTS

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Objectives

- To develop a synergistic framework for fixed and mobile sensors to collaborate on scene understanding
- To perform a tight integration of perception and action and to advance cyber-physical systems by exploring a class of synergies across: control, video understanding, and data management under uncertainty
- To experimentally validate the framework for surveillance domain, using a testbed with autonomous agents

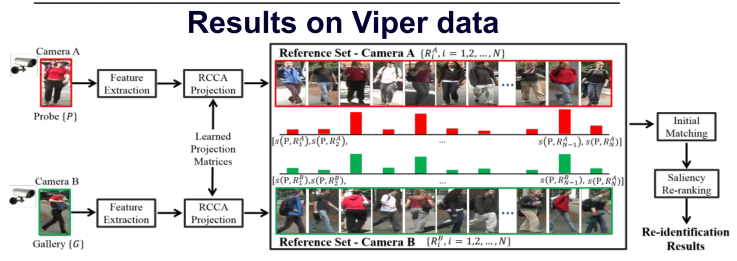
Recognizing People in non-overlapping Camera Network

- Direct feature comparison unreliable
- A reference set can be used to indirectly compare images from different camera views
- Regularized canonical correlation analysis (RCCA) finds the projection which maximizes correlation between the two sets of data
- A Robust method for computing RCCA is used to estimate covariance with limited training data
- Robust CCA provides better results than RCCA

(IEEE Trans. CSVT April 2016; IEEE SPL 2015)

Rank→	$r=1$	10	20	50	100
ROCCA (Proposed)	**30.44**	**75.63**	86.61	95.98	98.80
RCCA+RD [17]	30.25	74.68	**86.82**	95.70	**99.24**
SalMatch [30]	30.16	65.54	79.15	91.49	98.10
LAF [6]	29.60	69.30	84.50	**96.80**	99.00
RPLM [7]	27.34	69.02	82.69	94.56	98.54
RS-KISS [9]	24.50	66.60	81.70	93.50	98.00
CPS [31]	21.84	57.21	71.00	87.00	91.77
BiCov [32]	20.66	56.18	68.00	81.56	88.66
KISSME [16]	20.03	62.39	77.46	92.81	98.19
LMNN-R [33]	20.00	66.00	79.00	92.50	95.18
SDALF [4]	19.87	49.37	65.73	84.84	90.43
MRank [34]	19.34	55.51	70.44	87.69	96.90
PCCA [35]	19.27	64.91	80.28	95.00	97.01
DDC [36]	19.00	52.00	65.00	80.00	91.00
LMNN [37]	17.41	53.86	67.88	88.13	96.23
PRDC [8]	15.66	53.86	70.09	87.79	92.84
ITML [38]	15.54	53.13	69.05	88.54	96.93

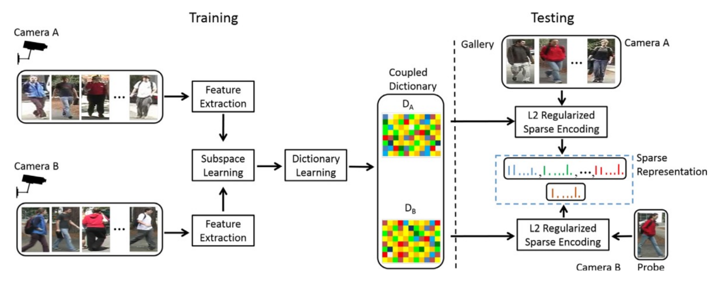
Results on Viper data

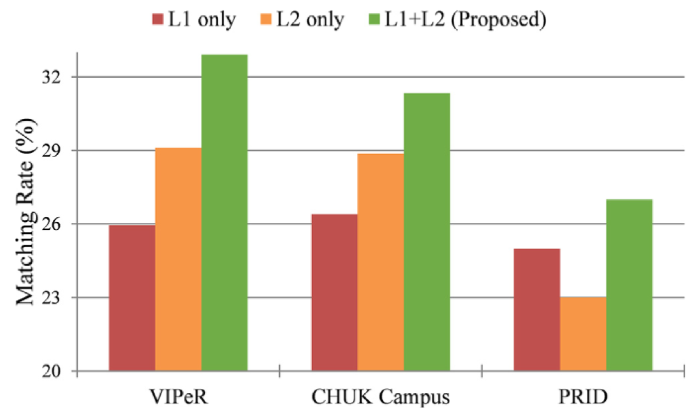


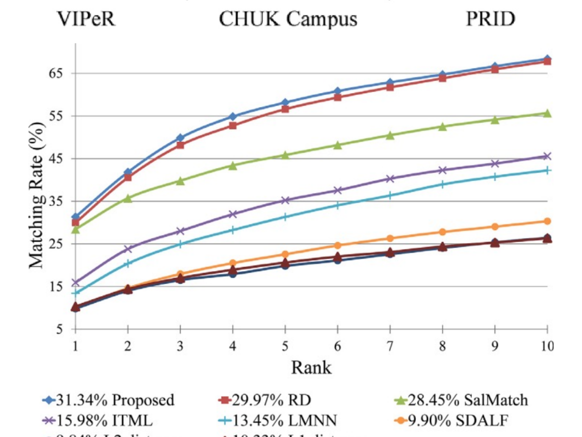
Sparse Representation for Re-Identification

- Two dictionaries are learned for each camera
- Sparse representation with L2 regularization are obtained using the coupled dictionaries which are used for matching
- Excellent results are obtained on several publicly available datasets

(Information Sciences, 355-356, 2016)







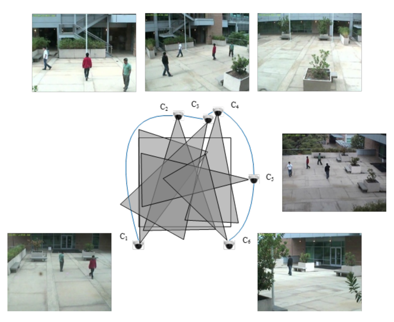
CMC curves on the CUHK Campus dataset

Distributed Estimation & Network Consistent Re-identification

Distributed Estimation

- The goal is to track targets in a distributed manner, using all the measurements.
- Distributed estimation schemes rely on exchanging information with neighbors.
- Neighboring cameras may not have same observations
- Proposed optimal estimation and data association scheme that can handle the case of limited observability.

(IEEE TPAMI, 2016)

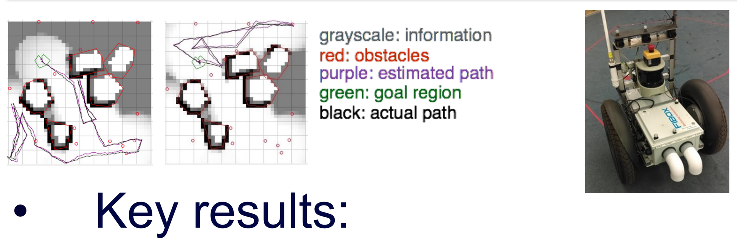


Network Consistent Re-Identification

- Can re-identification results be made consistent in a network?
  - Maximize global similarity across cameras with suitable consistency constraints.
- Will re-identification performance be improved by enforcing consistency?
  - Solve the problem using Binary Integer Programing

(IEEE TPAMI, 2016)

Exploration with Localization Guarantees



- Key results:
  - General info gathering framework
    - Maximizing information goals
    - Probabilistic guarantees
  - Asymptotic guarantees as the # of samples increases
  - Bound on the reward for partially known environments
    - Speeds computation (>1000x) to real time
  - Validation by simulation/ experiment

Path Optimization

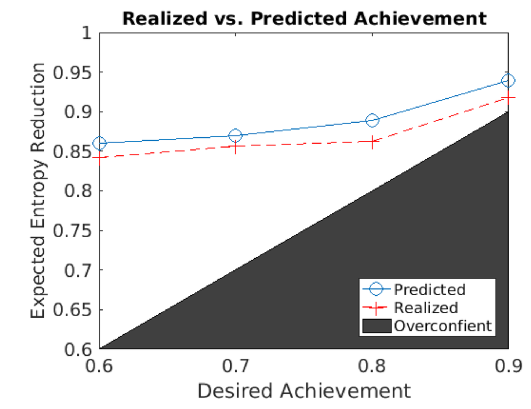
$$X^*_{t:T} = \text{argmax}_{X_{t:T}} R(X_{t:T})$$

Information Reward

$$R(X_{t:T}) = H(Y_{l(t)}) - \mathop{\mathbb{E}}_{Z_{t:T}}\left[H(Y_{n(T)})\right]$$

Information constraint

$$f(X_{t:T}) \leq C$$



Queries Over Uncertain Trajectories & Uncertainty in Stream Data Management

Assembling Queries

- Trajectories given on road networks with incomplete surveillance
- Only entry and exit times are known/specified for sub-regions
- If entry and exit times are obtained from observations or pre-specified- could objects of interest have assembled within the region for specified durations?
- Both top-k assembly sizes, top-k assembly durations are handled
- Use Contraction Hierarchies to speed up shortest distance
- We reduce query times by an order of magnitude over Dijkstra search

Stream Management

- Streams are of unbounded size - Cannot store entire stream, so cannot determine duplicates precisely
- Bloom filters (BF) useful, but cause false positives, & saturate quickly
- Our approach uses Bayesian analysis - We extend the analysis to infer item insertion times

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