SUPERVISED NEIGHBOURHOOD TOPOLOGY LEARNING (SNTL) FOR HUMAN ACTION RECOGNITION

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OUTLINE

- Introduction
- Problems
- Supervised Neighborhood Topology Learning (SNTL)
- Experiments and Analysis
- Conclusion

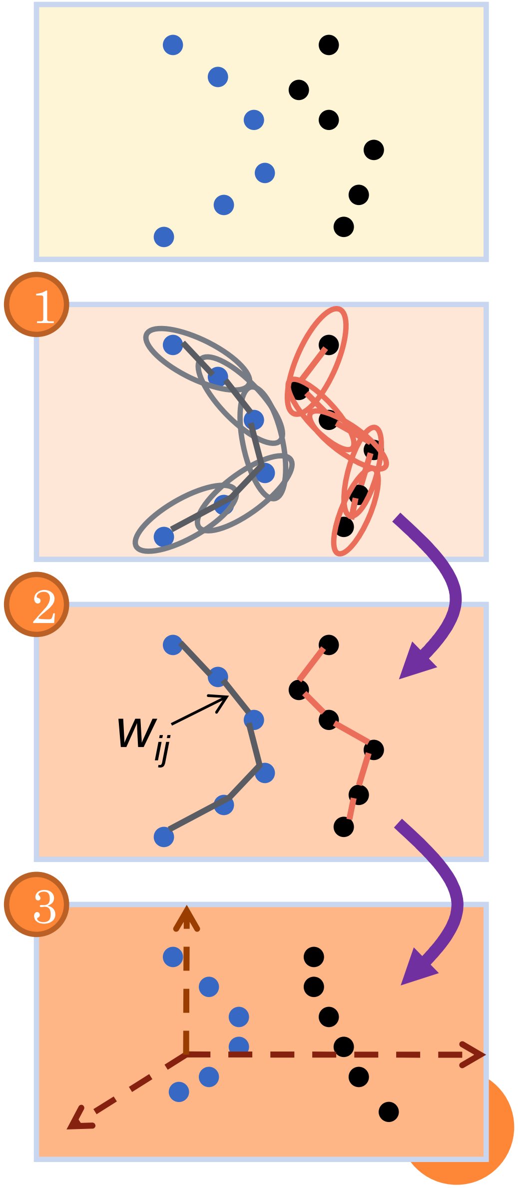
INTRODUCTION

INTRODUCTION

- Applications of Human Action Recognition
  - intelligent video surveillance
  - perceptual interface
  - content-based video retrieval
  - etc
- Existing Methods for Human Action Recognition
  - Flow based [AA Efros et al., ICCV 2003]
  - Template based [L. Gorelick et al., PAMI 2007]
  - Interest points based [J. Niebles et al., IJCV 2008]
  - Trajectory based [R. Messing et al., ICCV, 2009]
  - Manifold learning-based [Wang et al., TIP, 2007]
  - Etc
- Manifold learning-based methods (LPP and SLPP) achieved great success

LPP AND SLPP

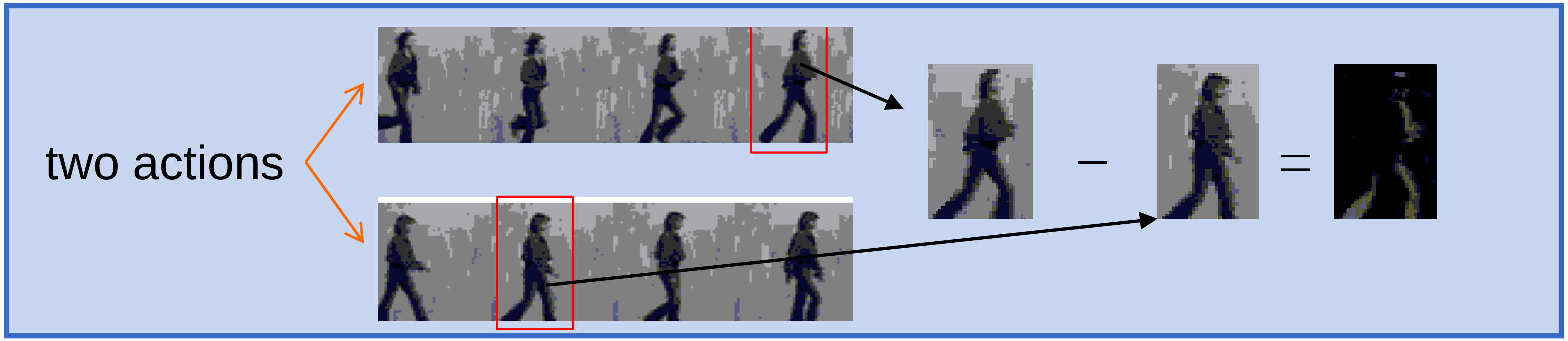
- Framework of LPP and SLPP
  - **1. Constructing the adjacency graph**
    - ε -neighborhood, KNN, or supervised
  - **2. Choosing the weights**
    - Simple-minded or heat kernel
  - **3. Eigenmaps**
    - Solve the optimization problem → projection matrix



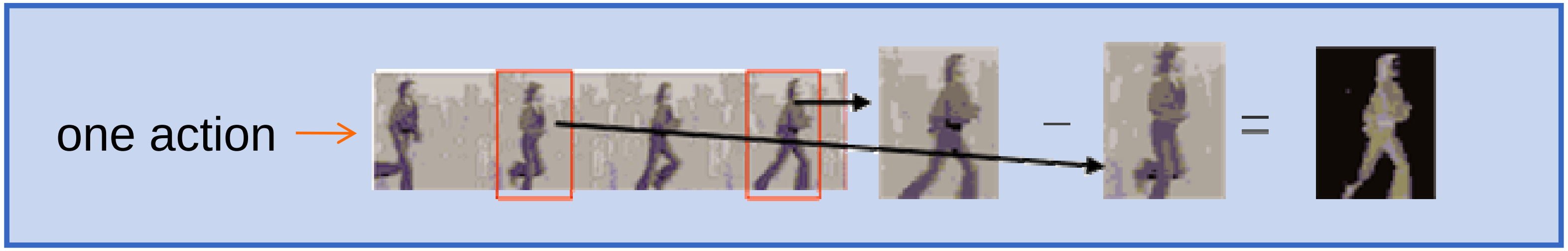
PROBLEMS

CHARACTERISTIC OF HUMAN ACTIONS

- similar pose in two different actions



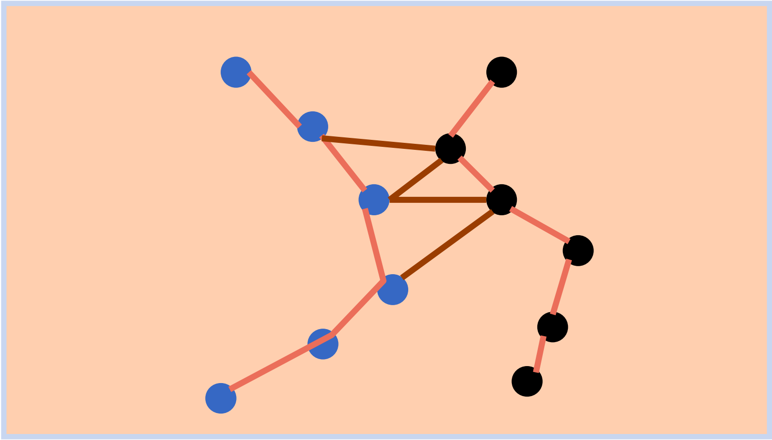
- dissimilar pose in the same action



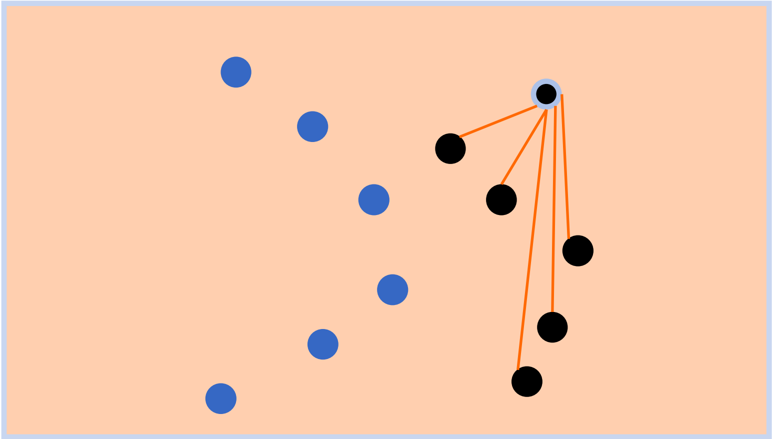
PROBLEMS IN LPP AND SLPP

- **adjacency graphs** play an important role in LPP and SLPP

LPP



SLPP



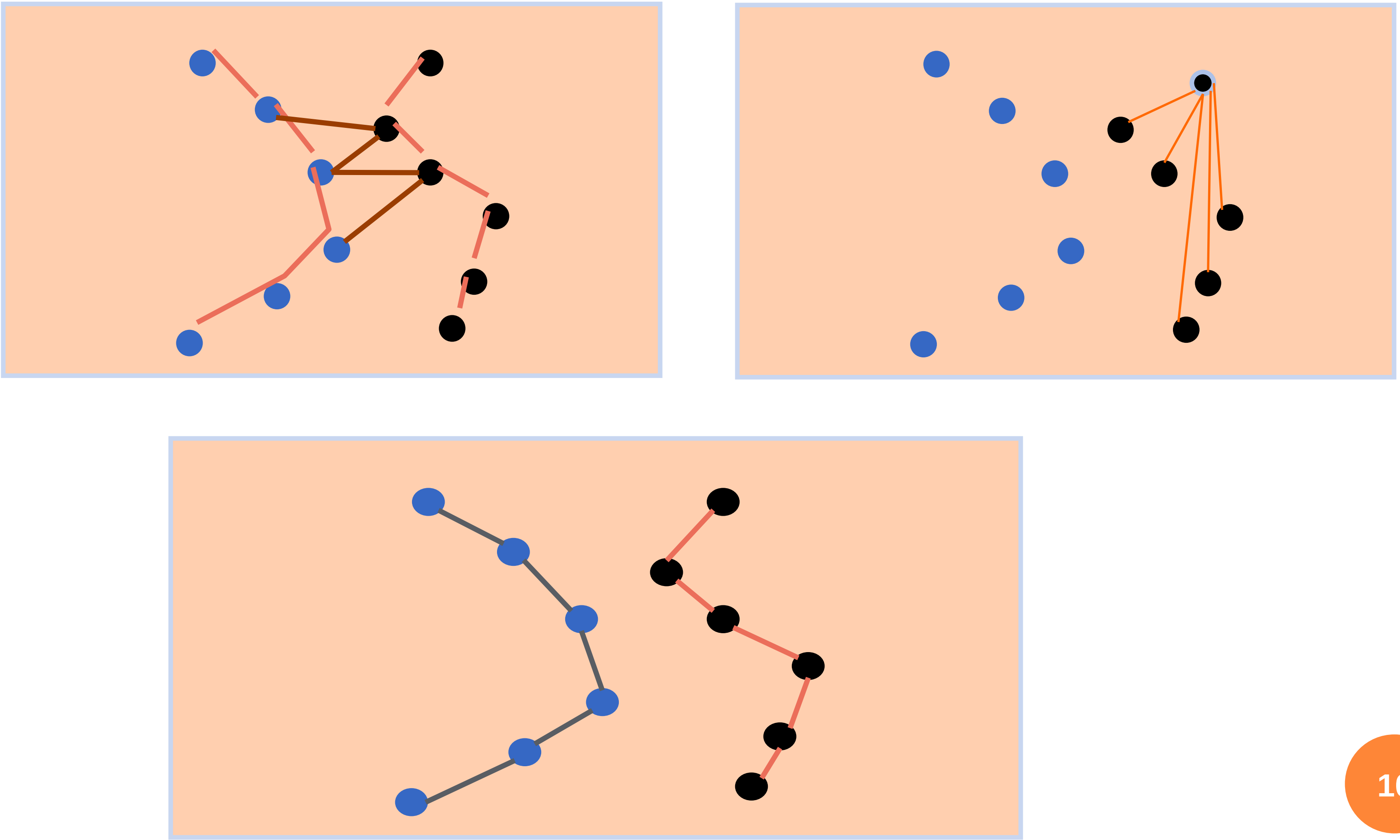
- in adjacency graph construction:
  - LPP only considers the local information
  - SLPP only considers the class information

PROPOSED METHOD

Reasonable adjacency graph

LPP

SLPP



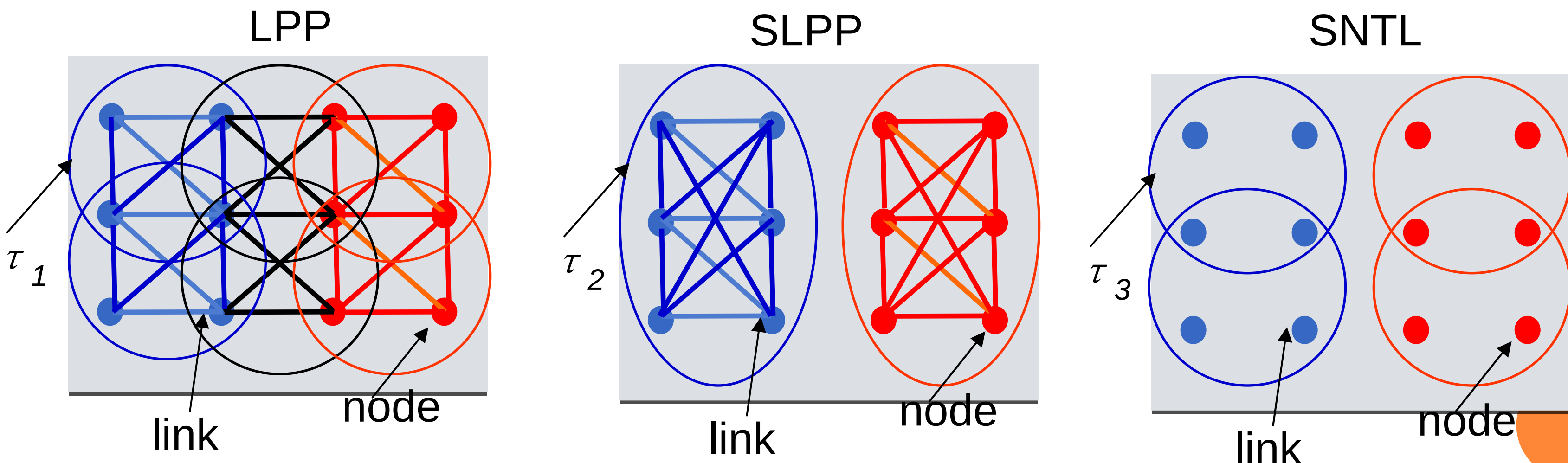
THE TOPOLOGY IN LPP AND SLPP

- the adjacency graph corresponding to a topology
- Data points with different topologies are considered to be different manifolds.
- denote: LPP → τ_1 , and SLPP → τ_2.
  - τ_1 : topology induced by Euclidean, *consider Euclidean distance* ←→ data close together are in the same neighborhood
  - τ_2 : topology induced by label information, *consider class distance* ←→ data point from same action are in the same neighborhood

    two class problem → $\tau_2 = \{\varnothing, S_1, S_2, S\}$
- integrate these two together?
- restrict the τ_1 on τ_2 *or* τ_2 on τ_1

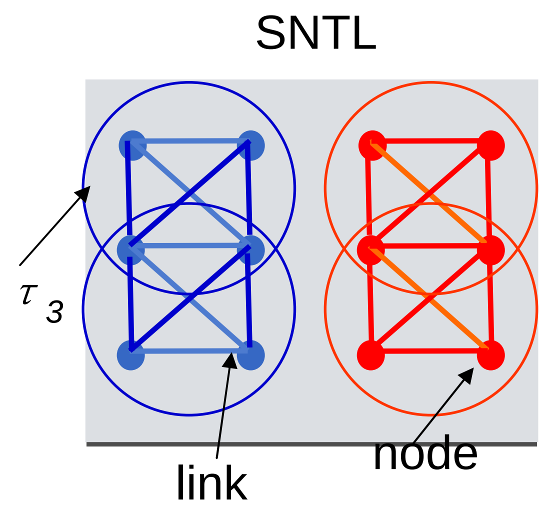
A NEW TOPOLOGY

- proposed method: define a new topology τ_3, so that make use of class label information and the local information
- *a subset is open* in τ_3 iff *it is the intersection of action data set S_i with an open set in the Euclidean space.*



ADVANTAGE OF NEW TOPOLOGY

- Keep the local information
  - temporal information
  - more suitable for manifold learning
- Keep the label information
  - recognition perspective
  - preserve the discriminative features



- make use of our new topology, and adopt the framework of LPP, we propose Supervised Neighborhood Topology Learning (SNTL)

ALGORITHMIC PROCEDURE

Proposed Neighborhood Topology Manifold Learning:

1. **Computing KNN parameter k_i for class i.** Choosing a percentage parameter a, $0<a<1$, let $k_i=aN_i$, where N_i denotes the sample number of class i.

2. **Putting edges on the graph.** An edge will be put between nodes t and s, if x_t and x_s belong to the same class i, and x_t is among the k_i nearest neighbors of x_s or x_s is among the k_i nearest neighbors of x_t.

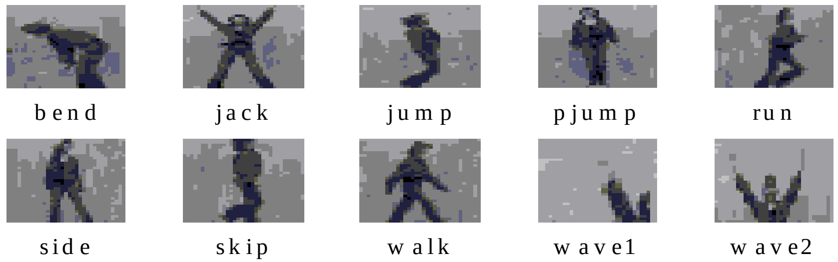
3. **Eigenmaps.** Optimize the cost function by EVD.

EXPERIMENTS

EXPERIMENT SETTING

Database	person num	action num	training	testing
Weizmann	9	10	8 persons	1 person

- leave-one-out rule
- example frames of different actions



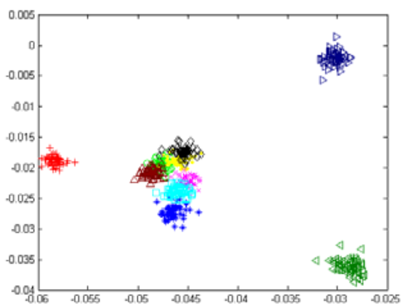
- Classifier: nearest neighbor framework with median Hausdorff distance

$$d(A_i, A_j) = S(A_i, A_j) + S(A_j, A_i),$$

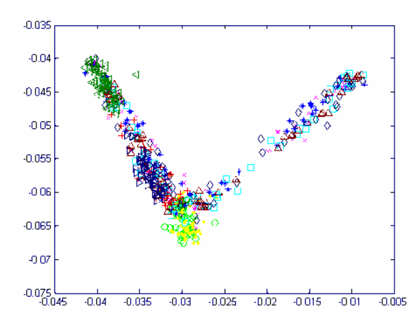
$$S(A_i, A_j) = \operatorname*{median}_k(\min_l(\|A_i(k) - A_j(l)\|))$$

COMPARATIVE EXPERIMENTS 1

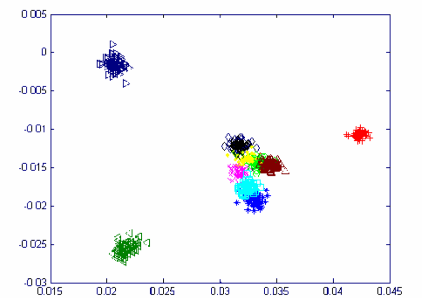
- 2D embeddings of training data bySNTL, LPP and SLPP



SNTL



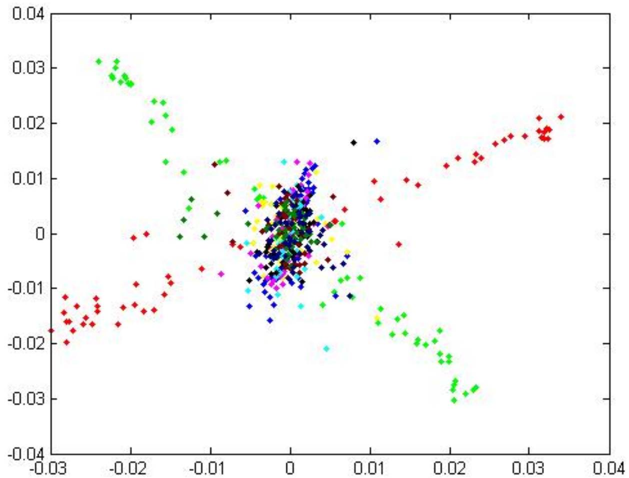
LPP



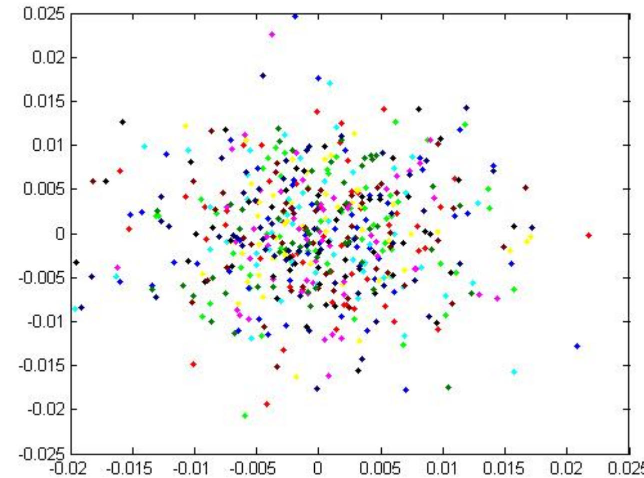
SLPP

- 2D embeddings of testing data by SNTL, and SLPP

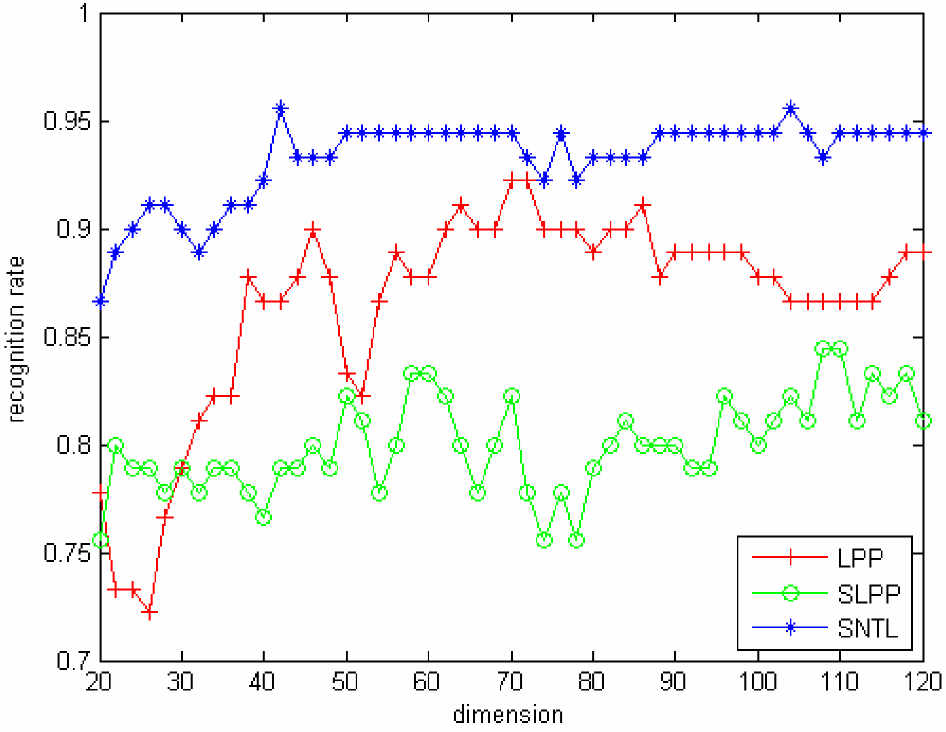
SNTL



SLPP



COMPARATIVE EXPERIMENTS 2



Recognition rate

method	LPP	SLPP	SNTL
Recognition rate (%)	92.22	84.84	**95.56**
Optimal dimension	70	108	42

CONCLUSION

CONCLUSIONS

- Propose a new supervised manifold learning method,
  - namely supervised neighborhood topology learning (SNTL)
  - for recognition perspective
- Advantages
  - preserves discriminative features
  - preserves temporal information of each action contained in local structure
- Disadvantages
  - Do not take full advantage of temporal information
  - Parameter is empirically determined

Thank you

Q & A ?