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Label Propagation on Facial Images Using Similarity and Dissimilarity Labelling Constraints

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Introduction

- Tagging facial regions with person ID in images and videos is useful for archival/search but time consuming when done manually.
- One approach that can be used is label propagation:
  - Manual labeling of faces with person ID in specific video frames or images
  - Spreading the labels from the (small) labeled facial image dataset to the unlabeled images.
  - Semi-supervised classification approach

Label Propagation Example

Figure: Propagate the labels from the manually labelled images (in rectangles) to the remaining ones.

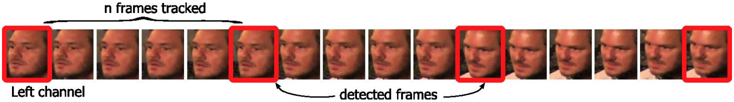
Overview

- **Goal:**
  Enhance classification performance (labeling accuracy) of the Multiple-graph Locality Preserving Projections – Cluster based Label Propagation (MLPP-CLP) technique (Zoidi et al [1]), when applied on facial images derived from stereo videos,
- **How:**
  Incorporate pairwise facial image similarity and dissimilarity constraints into the objective function of MLPP-CLP.

[1] O Zoidi, A Tefas, N Nikolaidis, and I Pitas, "Person identity label propagation in stereo videos," IEEE Transactions on Multimedia, vol.16, no. issue 5, pp. 1358–1368, 2014.

MLPP-CLP : Short Description

- Facial images are extracted by applying face detection and tracking in the left/ right view of a stereo video.
- Facial image trajectories are derived: sequences of facial images representing a tracked face over time.



- Each such facial trajectory is represented by one image (short trajectories) or more images (longer trajectories).

MLPP-CLP : Short Description

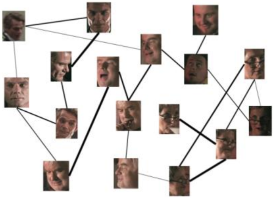
Inputs:

- Set of labeled facial images: $X_L = \{\mathbf{x}_i\}_{i=1}^{m_l}$
- Set of persons names (labels): $L = \{l_j\}_{j=1}^{Q}$
- Set of unlabeled data: $X_U = \{\mathbf{x}_i\}_{i=1}^{m_u}$
- Set of labeled and unlabeled facial images: $X = \{\mathbf{x}_1, ..., \mathbf{x}_{m_l}, \mathbf{x}_{m_l+1}, ..., \mathbf{x}_M\}, M = m_l + m_u$

Objective: spread the labels in L from the set of labeled data X_L to the set of unlabeled data X_U.

MLPP-CLP : Short Description

- MLPP-CLP: Extension of the Zhou et al[2] approach to data with multiple representations
- Facial images in stereoscopic video: K=2 data representations, left/right channel
- Build facial images similarity matrix **W** using heat kernel
- $W_{ij} = e^{-\frac{\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2}{\sigma}}, i \neq j, \mathbf{x}_i, \mathbf{x}_j \text{ are k-NN}$
- **W** represents the corresponding similarity graph (nodes=images)



[2] D. Zhou, O. Bousquet, T.N. Lal, J. Weston, and B. Scholkopf, "Learning with local and global consistency," NIPS 2004.

MLPP-CLP : Short Description

- Build matrix **Y** containing information regarding the labels in labeled data set X_L :

$$Y_{ij} = \begin{cases} 1, & \text{if image } i \text{ is labeled as } y_i = j \\ 0, & \text{otherwise.} \end{cases}$$

- Label Inference: Assign a score for every label to each facial image through matrix **F**:

$$\mathbf{F} = [\mathbf{f}_1^T, ..., \mathbf{f}_M^T]^T \in \mathbf{R}^{M \times Q}$$

  - F_{ij}: score for j-th label in i-th image
  - Q: number of labels, M: number of images

MLPP-CLP : Short Description

- $\mathbf{F}$ is found by solving a minimization problem which leads to the following solution:

$$\mathbf{F} = (1 - a)(\mathbf{I} - a\mathbf{S})^{-1}\mathbf{Y},$$

- $\mathbf{S} = \mathbf{D}^{-1/2}\mathbf{W}\mathbf{D}^{-1/2}$
- $D_{ii} = \sum_j W_{ij}$ degree matrix
- Label y_i for i-th image: $y_i = \arg\max_{j \in 1,\ldots,Q} [f_{i1}, \ldots, f_{ij}, \ldots, f_{iQ}]$
  - Image is assigned the label with the highest score

MLPP-CLP : Short Description

- MLPP-CLP extends this approach to data with multiple representations,
- A separate graph is constructed for each of the K facial image representations
  - $K = 2$ for stereoscopic images: left / right view.
- Each graph is represented by the corresponding similarity matrix $\mathbf{W}_k, k = 1, ..., K$
- The regularization framework takes the form:

$$Q(\mathbf{F}, \tau) = \frac{1}{2}\sum_{k=1}^{K} \tau_k tr(\mathbf{F}^T \mathbf{L}_k \mathbf{F}) + \mu tr((\mathbf{F} - \mathbf{Y})^T (\mathbf{F} - \mathbf{Y})),$$

- $\mathbf{L}_k = \mathbf{D}_k - \mathbf{W}_k$: graph Laplacian for the k-th data representation.
- τ_k, $k = 1,...,K$: weight for the k-th data representation

MLPP-CLP : Short Description

- This leads to the following solution for **F**:
  - $\mathbf{F} = (1 - a)\left(\mathbf{I} - a \sum_k \tau_k \mathbf{S}_k\right)^{-1} \mathbf{Y}$
  - $\mathbf{S}_k = \mathbf{D}^{-1/2}\mathbf{W}_k\mathbf{D}^{-1/2}$
- MLPP also performs dimensionality reduction by extending Locality Preserving Projections (LPP) method[3] to a multiple-graph framework
- A single projection matrix **A** is constructed for all data representations, while preserving locality information and similarity/dissimilarity constraints.

[3] X. He, P. Niyogi, "Locality Preserving Projections", NIPS 2003

Proposed method: Constrained MLPP-CLP

- Proposed Constrained MLPP-CLP (CMLPP-CLP) approach incorporates pairwise image similarity and dissimilarity constraints in the MLPP-CLP objective function.
  - Similar images shall be assigned the same label:
    - S: set of similar facial image pairs:

$$S = \{(i, j) | \mathbf{x}_i, \mathbf{x}_j \text{ must have the same label}\}$$

    - S contains facial images belonging to the same facial image trajectory
  - They depict the same actor

Proposed method: Constrained MLPP-CLP

- Dissimilar images shall be assigned different labels:
  - D: set of dissimilar pairs:

$$D = \{(i, j) | \mathbf{x}_i, \mathbf{x}_j \text{ must have different labels}\}$$

  - D includes facial image pairs that appear on the same frame
    - They belong to different actors.

Proposed method: Constrained MLPP-CLP

- Two weight matrices $\mathbf{W}_s$, $\mathbf{W}_d$ are constructed:

$$W_{s,ij} = \begin{cases} 1, & \text{if } (i,j) \in S \\ 0, & \text{otherwise,} \end{cases}$$

$$W_{d,ij} = \begin{cases} 1, & \text{if } (i,j) \in D \\ 0, & \text{otherwise.} \end{cases}$$

Proposed method: Constrained MLPP-CLP

- Similarity and dissimilarity information is propagated to neighboring nodes according to an iterative procedure that converges to the steady state solution:

$$\mathbf{F}_s = (1-\alpha)(\mathbf{I}-\alpha\mathbf{P})^{-1}\mathbf{W}_s$$

$$\mathbf{F}_d = (1-\alpha)(\mathbf{I}-\alpha\mathbf{P})^{-1}\mathbf{W}_d.$$

- $\mathbf{P} \in \Re^{M\times M}$: sparse neighborhood probability matrix:

$$P_{ij} = \begin{cases} \frac{1}{|N_i|} & \text{if } j \in N_i \\ 0, & \text{otherwise,} \end{cases}$$

- N_i: neighborhood of node i

Proposed method: Constrained MLPP-CLP

- Then dimensionality reduction is performed through MLPP.
- Label propagation is conducted on the data projections, by incorporating the pairwise similarity and dissimilarity constraints to the label propagation objective function:

$$Q(\mathbf{F}) = \frac{1}{2} tr(\mathbf{F}^T \left(\sum_{k=1}^{K} \tau_k \mathbf{L_k} + \beta \mathbf{L_s} - \gamma \mathbf{L_d} \right) \mathbf{F}) + \\ \mu tr((\mathbf{F} - \mathbf{Y})^T (\mathbf{F} - \mathbf{Y}))$$

- $\mathbf{L}_s = \mathbf{D}_s - \mathbf{F}_s$, $\mathbf{L}_d = \mathbf{D}_d - \mathbf{F}_d$: graph Laplacians of the similarity and dissimilarity constrains.

Proposed method: Constrained MLPP-CLP

- Minimization of $Q(\mathbf{F})$ leads to the following solution for $\mathbf{F}$:

$$\mathbf{F} = \mu \left(a\mathbf{I} + \sum_{k=1}^{K} \tau_k \mathbf{L}_k + \beta \mathbf{L}_s - \gamma \mathbf{L}_d \right)^{-1} \mathbf{Y}.$$

Experimental evaluation

- Dataset:
  - 3 stereo movies
  - Duration: 2 hours each
  - Facial images per movie: 5300, 3500, 5000 (after retaining one/more image(s) per facial trajectory)
  - Actors (classes) per movie: 26, 44, 58.
- 5% of the facial images were manually labeled.
- Dimensionality reduction down to 75 dimensions

Experimental evaluation

	MLPP-CLP	CMLPP-CLP
Movie 1	0.7859	**0.801223**
Movie 2	0.6395	**0.672213**
Movie 3	0.62	**0.710133**

Classification accuracy obtained using MLPP-CLP and Constrained MLPP-CLP (CMLPP-CLP).

- Incorporation of pairwise constraints into the objective function of label propagation increases the classification accuracy by **4.6%** on average.
- Recent experiments showed that CMLPP-CLP outperforms both older and recent approaches
  - OMNI-Prop, Yamaguchi et al., AAAI 2015
  - CAMLP, Yamaguchi et al., SIAM Int. Conf. on Data Mining, 2016
  - MLAN, Nie et al, AAAI 2017

Choice of ”constraints vs labels” strategy

- A human annotator can perform two different actions towards reaching a desired classification accuracy:
  - Manually label additional unlabeled images or
  - Place additional pairwise facial image similarity or dissimilarity constraints
- Experiments were conducted in order to answer the following questions:
  - What is the effect of inserting one or more constraints or labeling one or more images?
  - Which of the two actions is more beneficial?

Choice of ”constraints vs labels” strategy

- N_{RL}: current number of manually labeled images
- N_{TL}: number of manually labeled images required in order to reach the desired classification accuracy P (without using pairwise constraints)
- N_c: number of pairwise similarity constraints needed (in addition to the N_{RL} labeled images) in order to reach P
- Ratio r of additional labeled images over additional constraints for achieving desired classification accuracy:

$$r = (N_{TL} - N_{RL})/N_c$$

- Small r (below 1): more constraints than labels are needed in order to reach the desired accuracy P

Choice of ”constraints vs labels” strategy

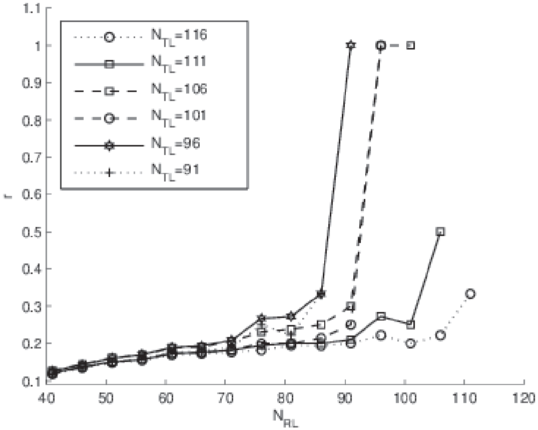


Figure: r versus N_{RL} for various values of N_{TL} (desired accuracy P).

Choice of ”constraints vs labels” strategy

- r is in most cases significantly below 1:
  - Less labeled images than labeling constraints are neededto reach the desired accuracy
  - Labeled images carry more information than constraints.
- However, the effort of labeling an image is larger than that of assigning a pairwise labeling constraint.

Conclusions

- A novel method (CMLPP-CLP) for propagating person identity labels on facial images extracted from stereo videos was introduced.
- It incorporates similarity and dissimilarity labelling constraints in order to increase the classification accuracy
- The proposed method outperforms current methods.
- It can be used to perform label propagation in other types of images or data in general.
- It can be easily adapted to work with images taken from monocular cameras.
- An investigation of labels vs constraints strategy that should be followed in order to reach a desired accuracy was also conducted.

Conclusions

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Thank you for your attention!