Facial Expression Detection using Patch-based Eigen-face Isomap Networks

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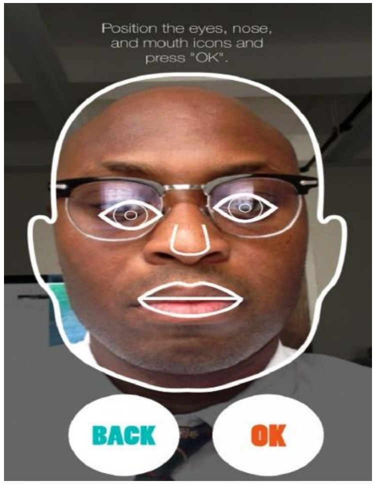
Outline

- Introduction
- Facial Patch Creation
- Eigen-Face Creation
- Facial Network Clustering
- Facial Network Analysis
- Results
- Conclusions

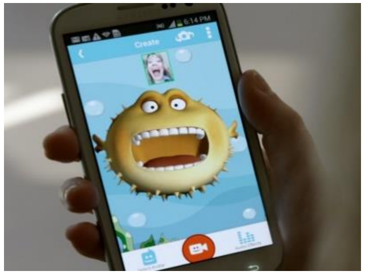
Introduction

- Automated Facial Expression Detection:
  - Useful for Real Time Security Surveillance Systems, Social Networks [1].
- Challenges due to variations in:
  - Pose
  - Lighting
  - Imaging distortions
  - Expression
  - Occlusions.
- Motivation:
  - Patched faces have better expression clustering performance than full faces.
  - Clustering minimizes training data complexity.
- Goal:

  To design a network-based expression classification system with low computational time complexity.



Source:http://mostepicstuff.com/app-that-changes-your-facial-expression-to-cartoon-look/



Source:http://www.smithsonianmag.com/innovation/app-captures-emotions-real-time-180951878/?no-ist

Prior Work

- Two categories of existing facial expression detection algorithms:
  1. Based on extracting feature vectors from parts of a face such as eyes, nose, mouth, and chin, with the help of deformable templates [2] [3].. High computational complexity
  2. Based on the information theory concepts such as principal component analysis method [4-6]. Not very effective. Large training data set required.

- The proposed method involves:
  - Guided patch creation followed by Isomap clustering of the patched Eigen-faces for unsupervised classification.
  - Two classification tasks are performed:
    1. Classification of images with occlusions (mainly glasses and beards)
    2. Classification of smiling faces.

  - Low computational time complexity:
    - Unsupervised classification requires a runtime of less than 1 second for a dataset of 80 images of original dimension [112x92] each, in a 2.6GHz 2GB RAM Laptop.

Key Contributions

1. Facial Expression Network-based clustering requires only 2 training data samples for expression clustering.

2. Facial Expression Network analysis identifies the faces at the edge of the expression clusters as vital expression detectors. Network centrality and flow-based measures can further demonstrate the expression information flow in the networks.

Data Set: 80 images corresponding to the 1st and 10^{th} image per person for 40 people [2x40=80 images] used from the ORL Data base of faces [7]. Each image of dimension [112x92] is resized to [90x90] for computational simplicity.

Facial Patch Creation

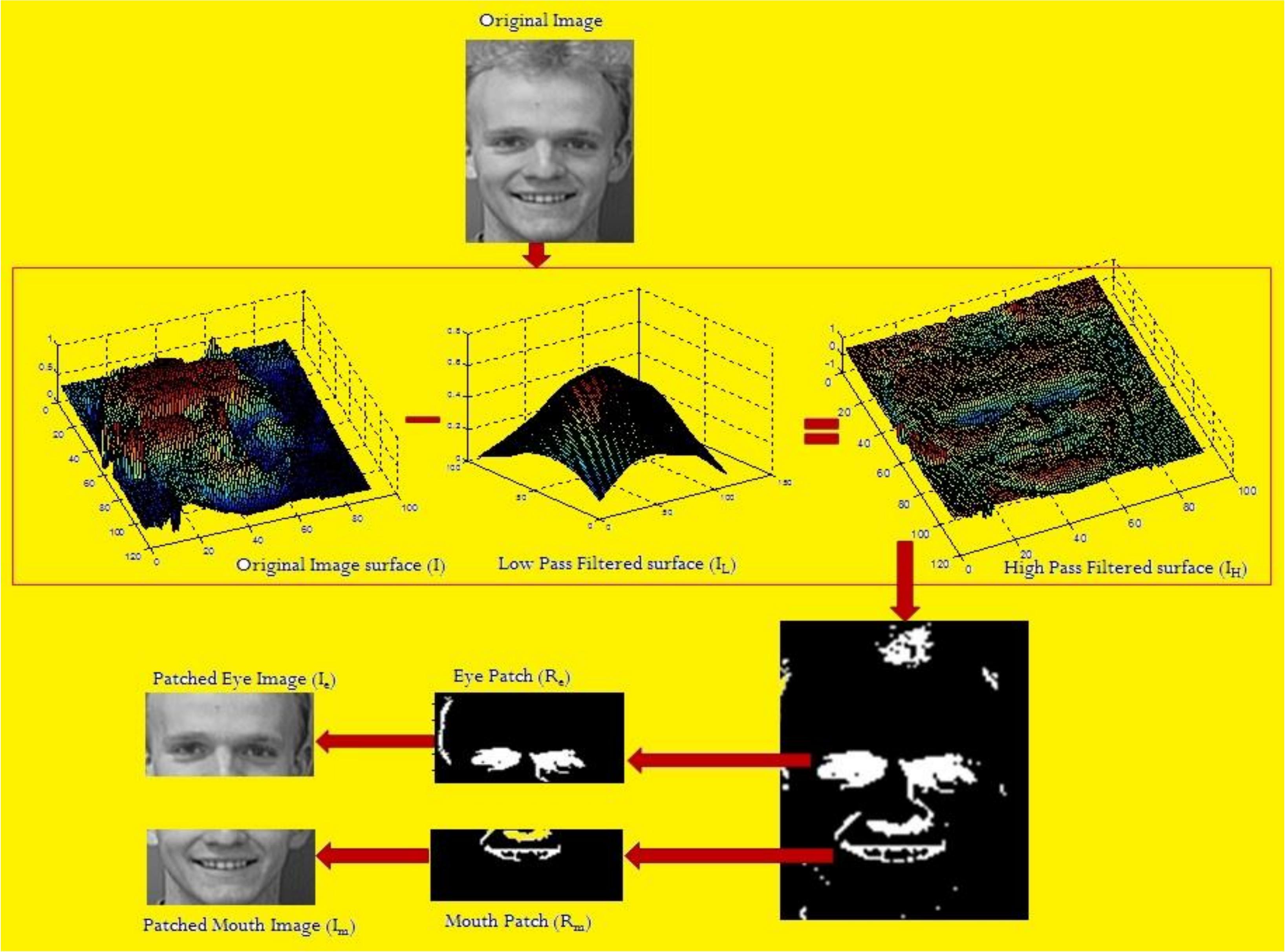


Fig 1: Extraction of high pass filtered regions of interest and face patches corresponding to the eye and mouth region, respectively.

Eigen-Face Creation [6]

- For each image 'I', the Karhunen-Loeve expansion [4] is applied to find vectors that best represent the distribution of face images $\{I_1, I_2, ...I_n\}$, where n=80 images.
- The average face is the 0th Eigen vector computed as: $\mu_I = \frac{1}{n}\sum_{i=1}^{n} I_i$
- Difference of each face from the average are computed: $\phi_i = I_i - \mu_I$

  $\{\upsilon_i\}_{i=1}^{n}$ are subjected to PCA to find a set of 'n' orthonormal vectors

  $\{\phi_i\}_{i=1}^{\ n}$ which best describe the distribution of images.
- **Method:**

Let covariance matrix: $C_{ov} = \frac{1}{n}\sum_{i=1}^{n} \phi_i \phi_i^T = AA^T, A = [\phi_1, \phi_2, ...\phi_n]$

For computational feasibility: $A^T A v_i = \lambda_i v_i \Rightarrow AA^T A v_i = \lambda_i A v_i \Rightarrow A v_i$ are eigen vectors of C_{ov}

- Construct a matrix of dimension [nxn] as $L = A^T A$, where, $L_{l,m} = \phi_l^T \phi_m$
- 'n' Eigen-vectors of `L' ($\{\upsilon_i\}_{i=1}^{n}$) are then extracted. These Eigen-vectors determine linear combinations of 'n' faces to form the Eigen-Faces ($\rho_i\}_{i=1}^{n}$) .

where, $\rho_i = \sum_{j=1}^{n} \upsilon_{i,j} \phi_j$

- Matrix 'L' represents signature of each face in terms of an 'n' dimensional vector.

Example of Eigen-Faces

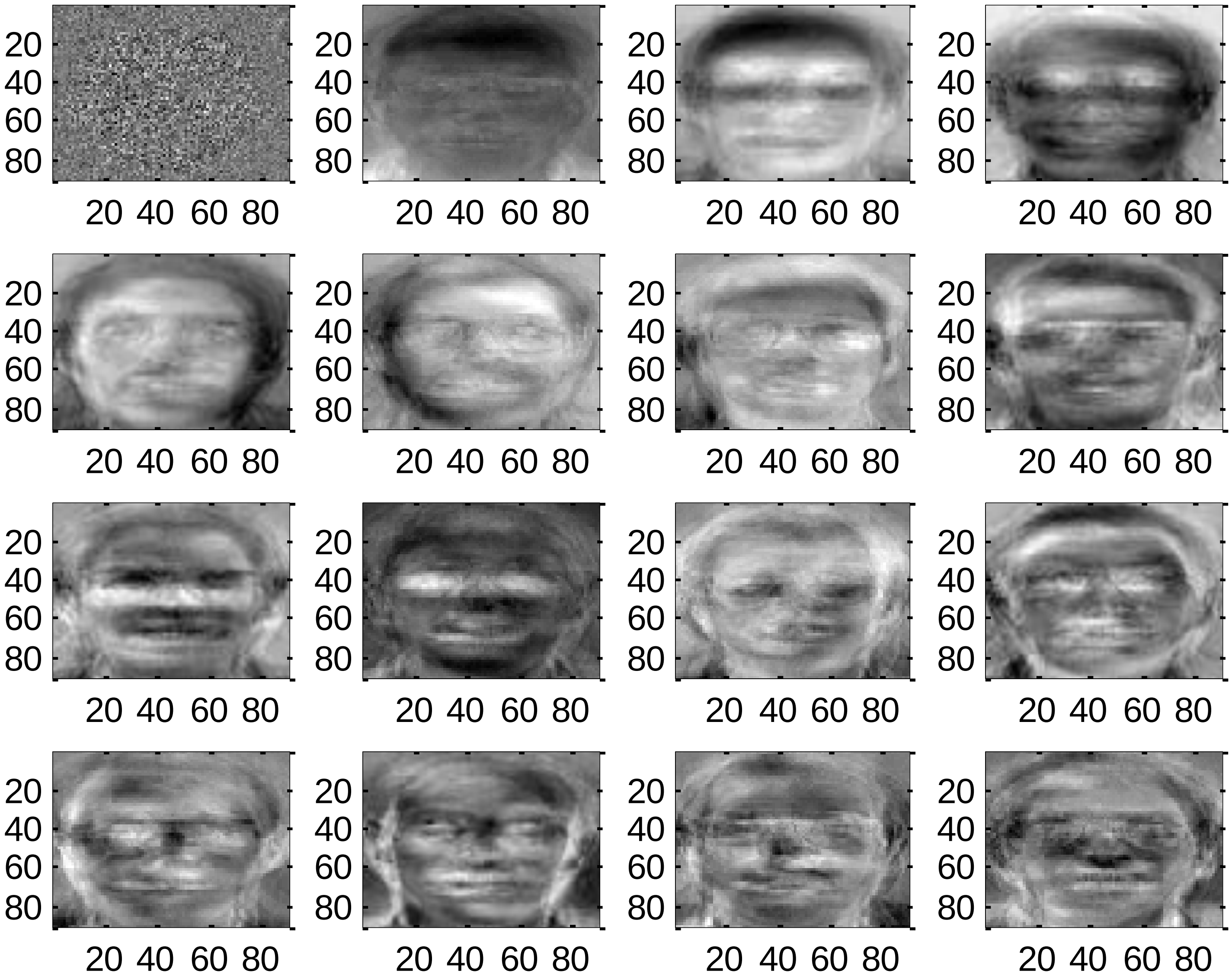


Fig 2: The 0th Eigen vector followed by 15 Principal Eigen-Faces for the 1st face of 1st person in the ORL data set.

Isomap-based Clustering

- For the $L_{[nxn]}$ matrix, Isomap [8] is used for lower dimension embedding using multidimensional scaling.
- Matrix 'L' is reduced to an unweighted network (G), where each image 'i' is connected to 'k' Euclidean neighbors in high dimensional space.
- Network G=(Y,E), where $Y_i\}_{i=1}^{n}$ represent the signature of each Eigen-Face as a vertex/node. 'E' represents an edge matrix such that

$$E_{o,p}\begin{cases}=1: \text{represents a directed link between nodes } Y_o, Y_p \\ =0: \quad \text{represents no link between nodes } Y_o, Y_p\end{cases}$$

- Two faces (nodes) that have the largest Euclidean distance between them are selected as cluster representatives. i.e.,

If, $D_{i,j}$ represent the distance between nodes (i,j), then, $\{Z_i, Z_2\} = \arg\max_{i,j} D_{i,j}$
Such that Z_1 belongs to cluster 1 and Z_2 belongs to cluster 2.

- Based on the distance of every other node from Z_1 or Z_2 , each node is assigned to the closest cluster.

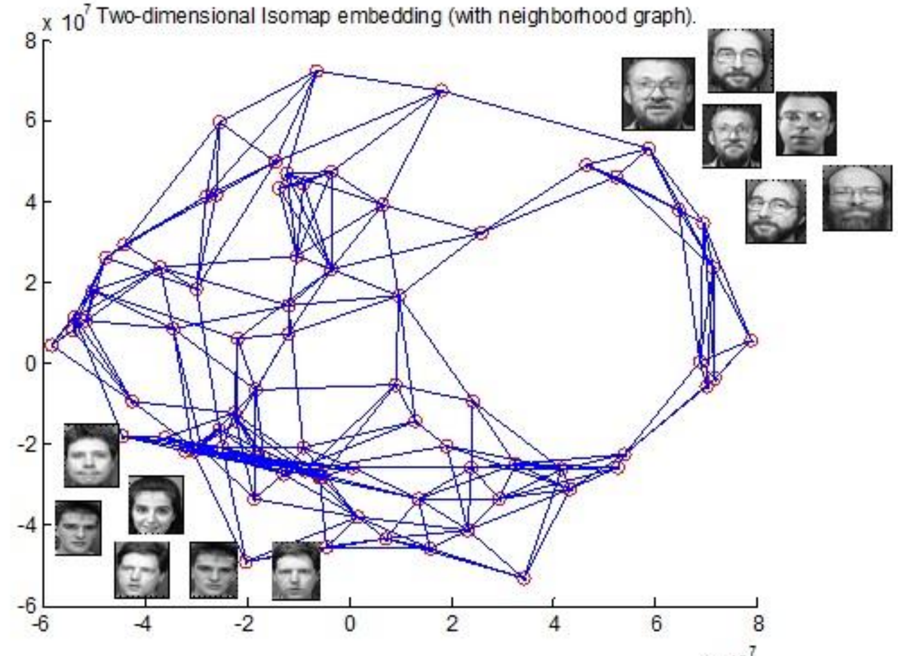


Fig 3: Isomap-based clustering using full faces

Results

Task 1: Eye occlusion detection (classification of faces with glasses)

- Comparison of Isomap-based clustering using full face Eigen-faces vs. Patched Eye (I_e) Eigen-Faces.

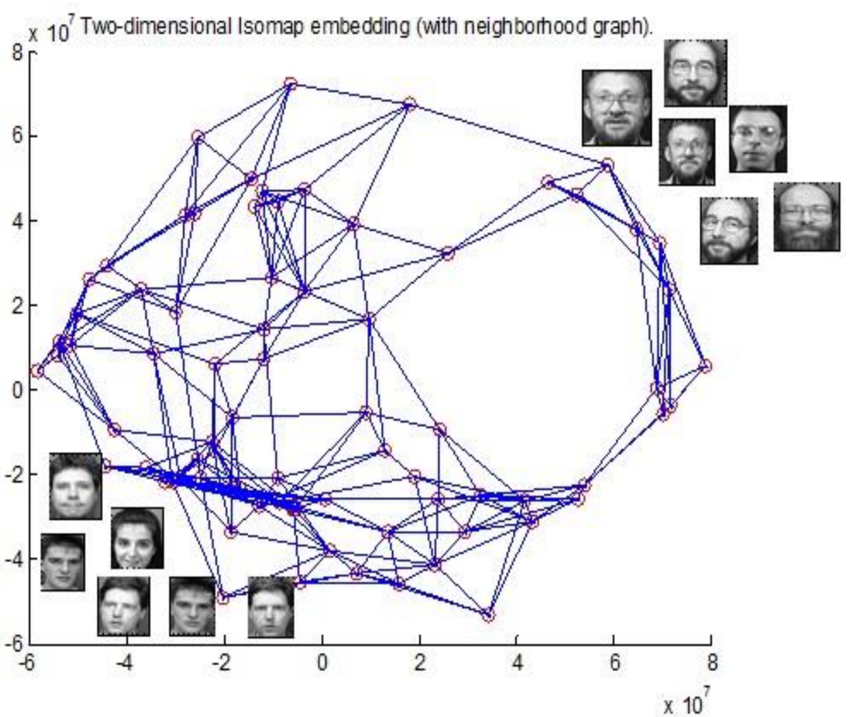


Fig 4a: Isomap-based clustering using full faces Isomap created using k=5

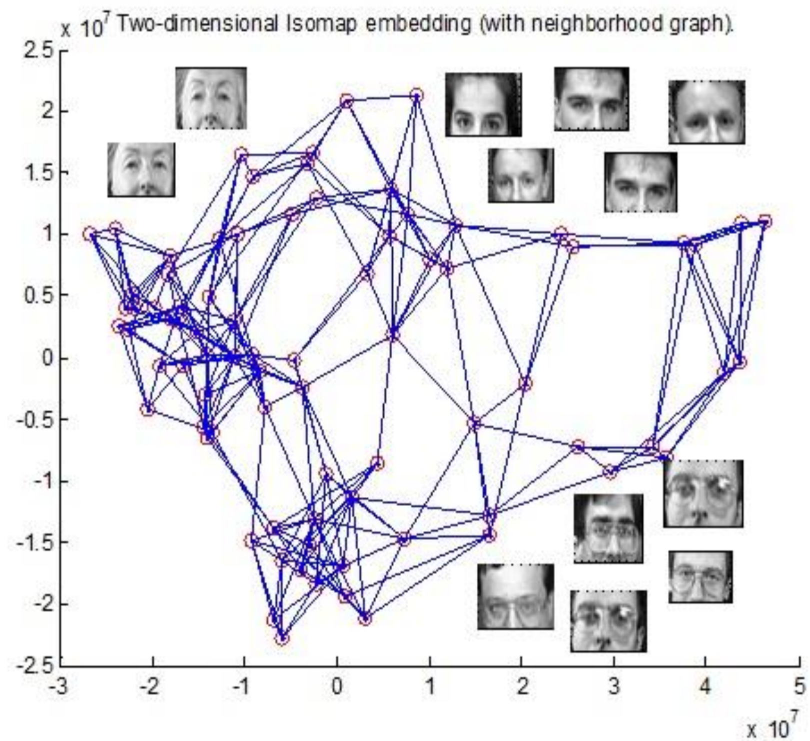


Fig 4b: Isomap-based clustering using patched faces. Isomap created using k=5

Task 2: Smile detection (classification of smiling faces)

- Comparison of Isomap-based clustering using full face Eigen-faces vs. Patched Eye (I_e) Eigen-Faces.

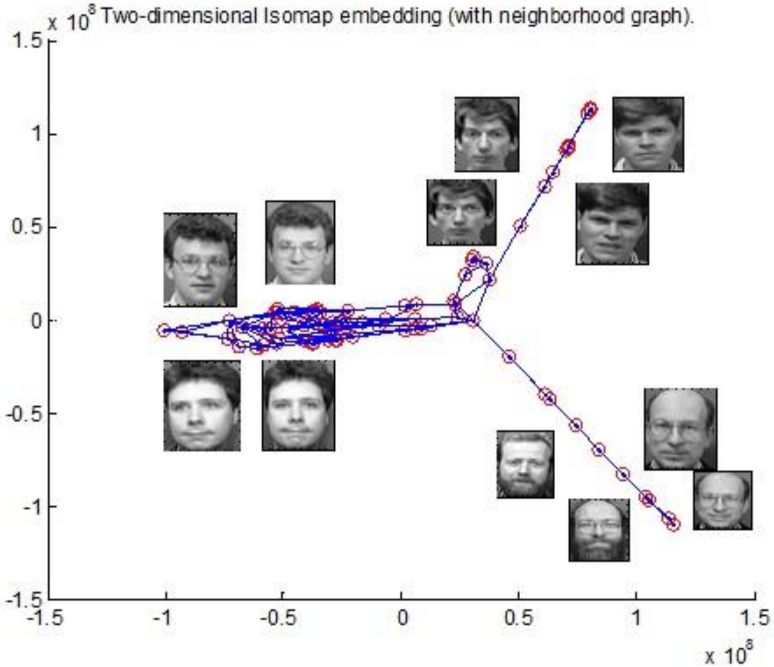


Fig 5a: Isomap-based clustering using full faces Isomap created using k=3

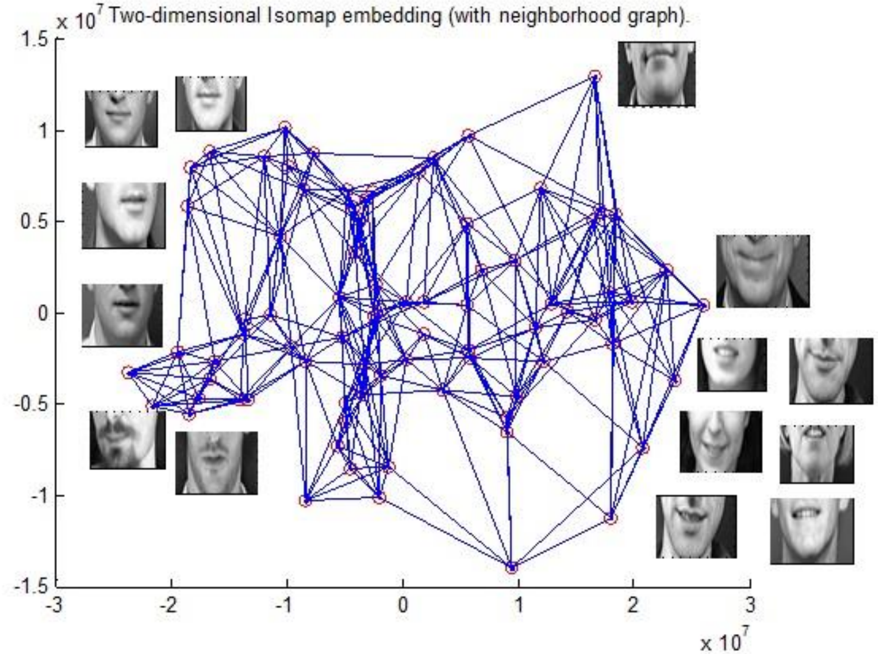


Fig 5b: Isomap-based clustering using patched faces. Isomap created using k=7

Method	Sensitivity	Specificity	Accuracy	k	Isomap Residual	AUC
Task1:	Classification of facial occlusions					
Full Face Eigen-Faces	0.6896	0.7450	0.725	5	0.0603	0.7031
Patched Eigen-Faces	0.7586	0.6862	0.725	5	0.0275	0.7245
Task 2:	Classification of smile					
Full Face Eigen-Faces	0.1428	0.8667	0.55	3	0.02605	0.5111
Patched Eigen-Faces	0.75	0.5556	0.6625	7	0.0132	0.6319

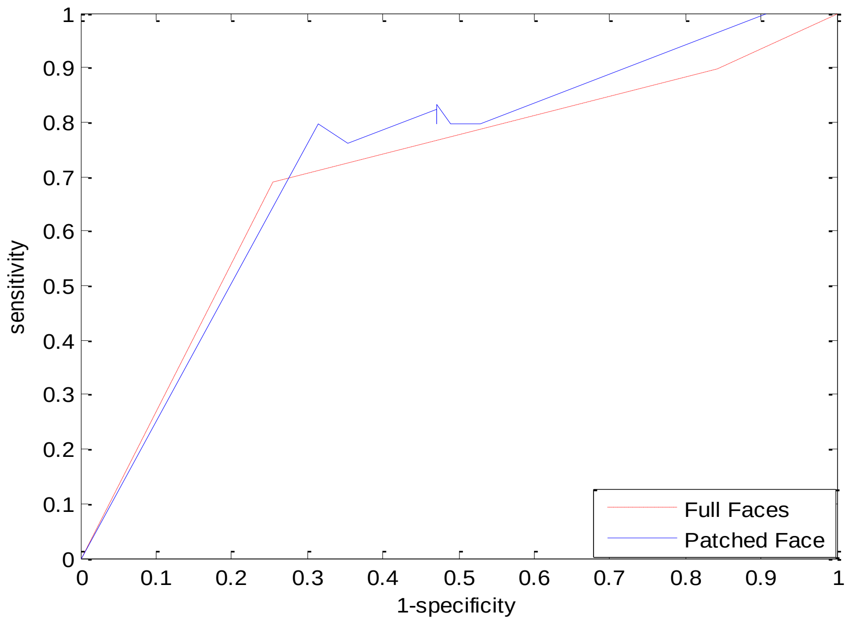


Fig 6a: Clustering ROC for Task 1 by varying parameter ‘k’ from [3-21]

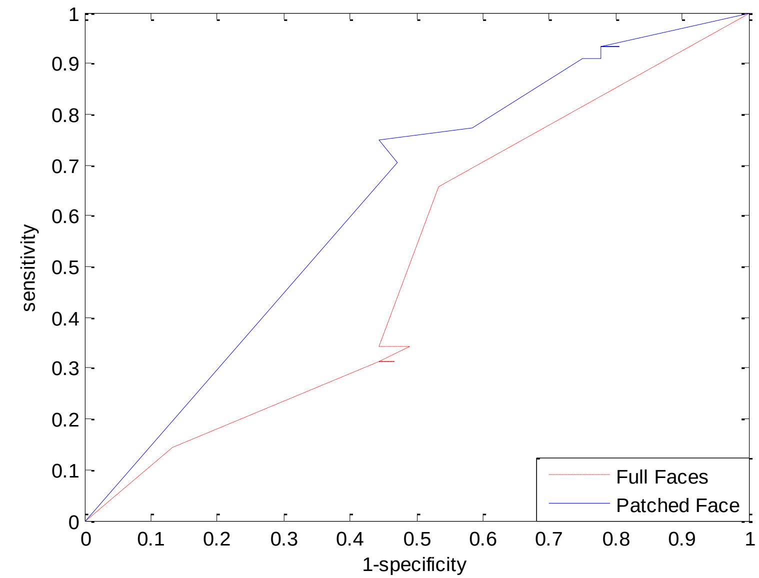
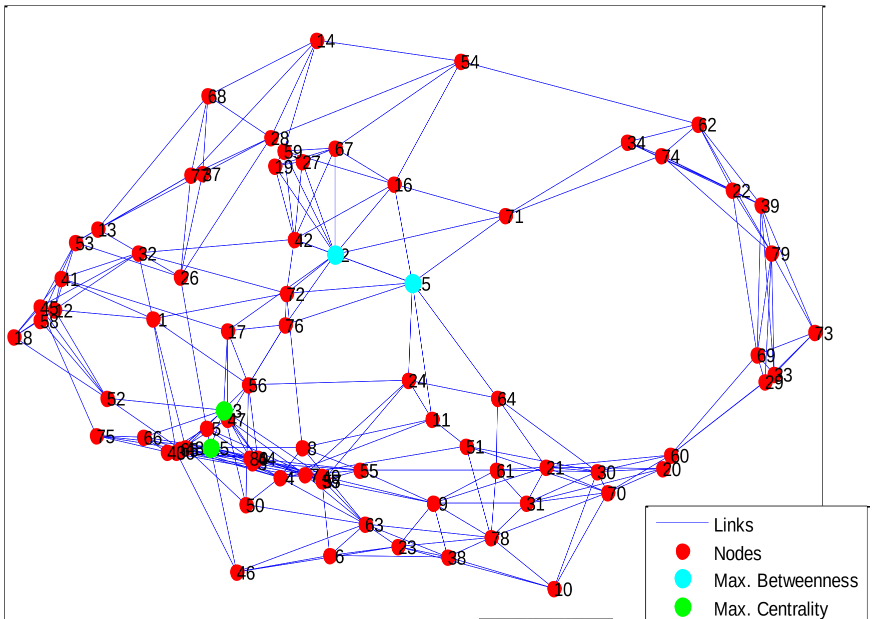


Fig 6a: Clustering ROC for Task 2 by varying parameter ‘k’ from [3-21]

Network Analysis

- The nodes(faces) with top 2 highest betweenness centrality(B) and Eigen Centrality (EC) are identified for the Facial Networks.
- Task 1: **Full Face Network**



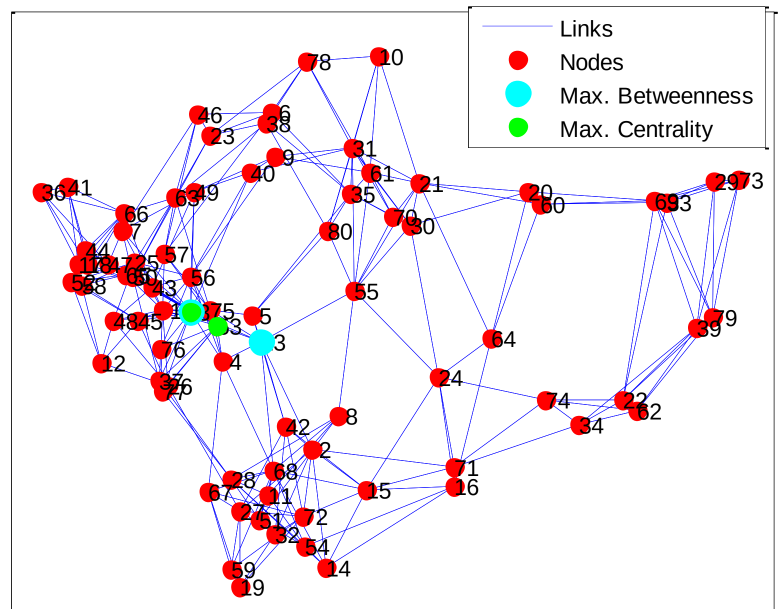
B_1=753.16

B_2=640.95

EC_1=0.27

EC_2=0.25

Patched Face Network



B_1=1154

B_2=1052

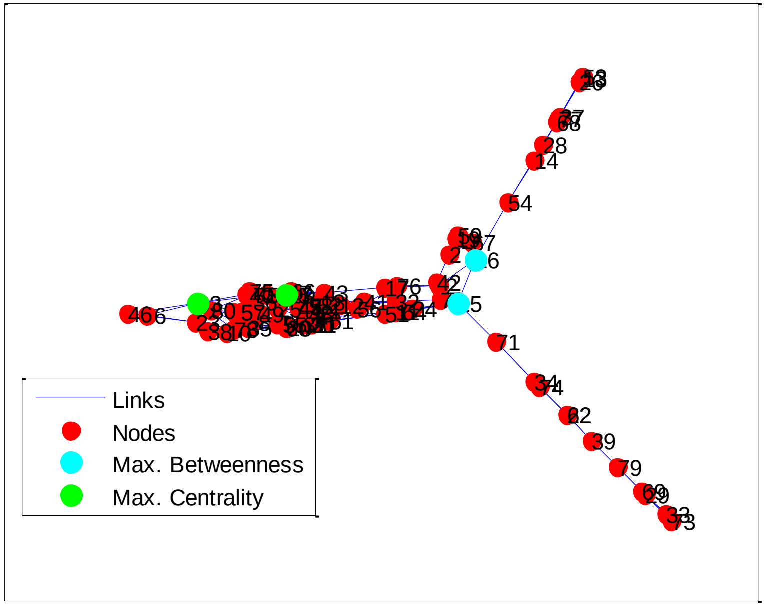
EC_1=0.3865

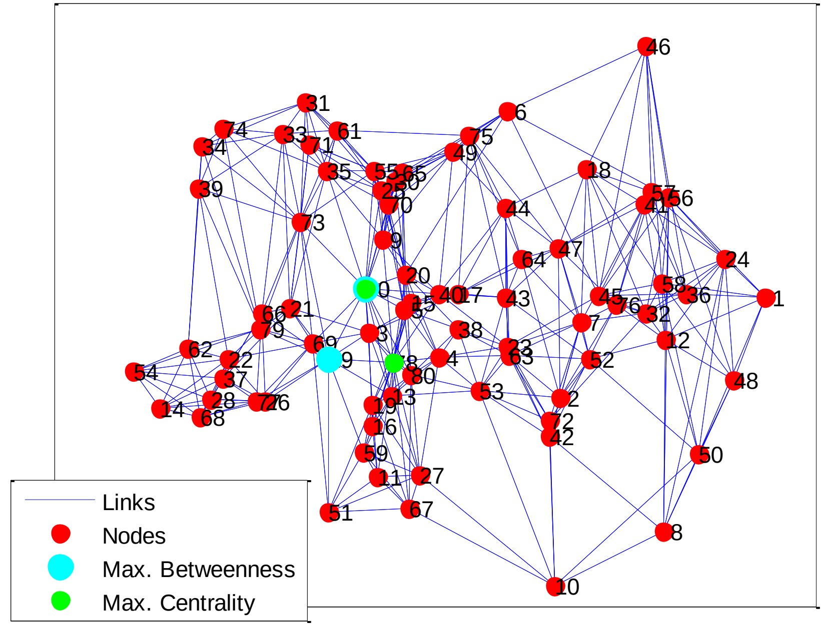
EC_2=0.3167

Patched faces have high centrality for occlusion clustering.

- Task 2: **Full Face Network**

Patched Face Network



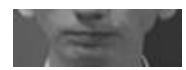


B_1=2629

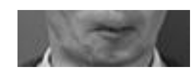
B_2=1588

EC_1=0.296

EC_2=0.292



B_1=703



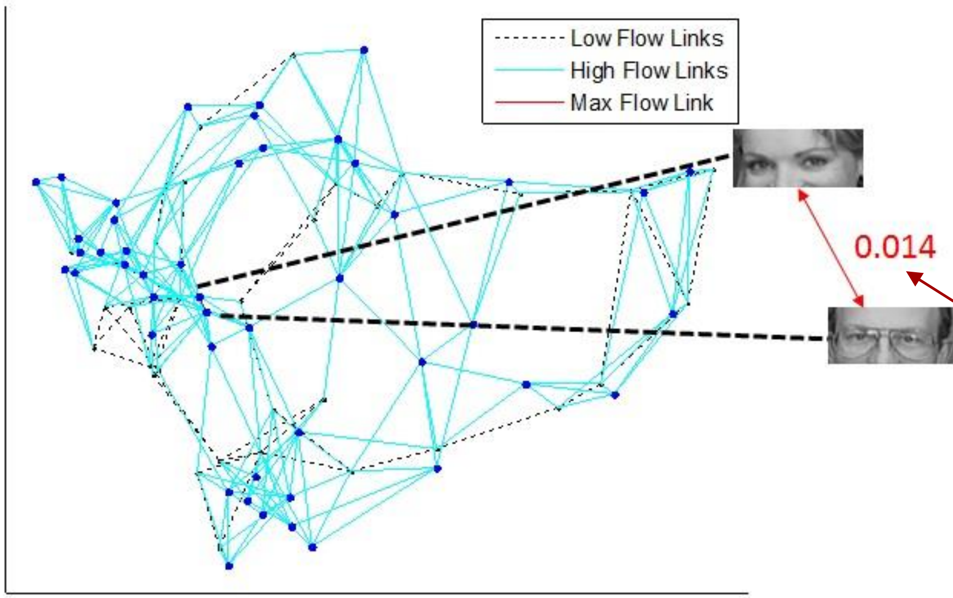
B_2=664

EC_1=0.3058

EC_2=0.2632

Patched faces have high centrality for smile clustering.

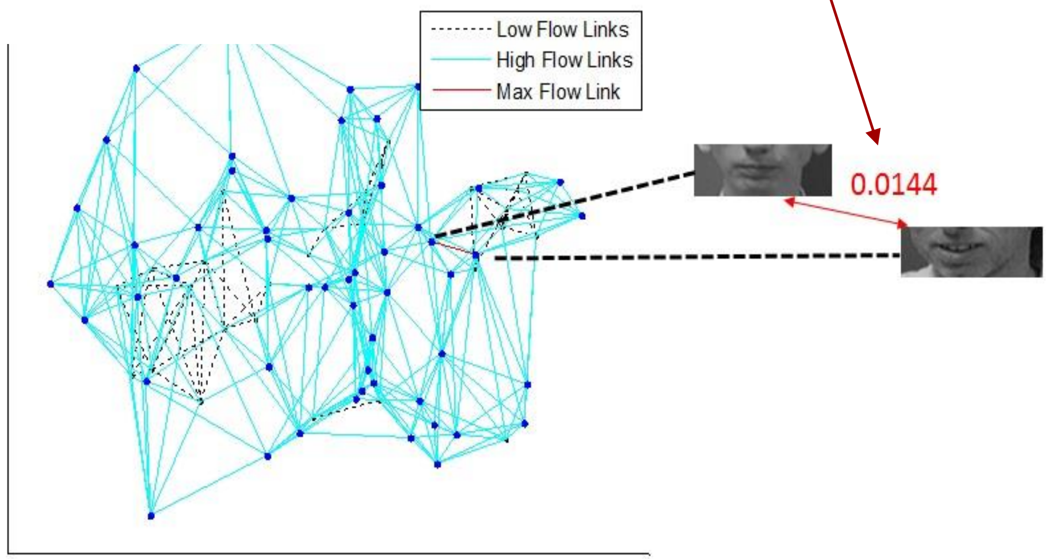
Information Flow in Patched Networks



- Task 1: Highest flow in the Patched Face Network is between a non-occluded female eye and occluded male eye.

Fraction of entire flow through the network

- Task 2: Highest flow in the Patched Face Network is between a non-smiling and partially smiling face



Conclusions

- Patched Eigen-face networks have better clustering performance for eye occlusion and smile detection than networks generated with full faces.

- The proposed patched Eigen-face based Isomap clustering technique achieves 75% sensitivity and 66-73% accuracy in classification of faces with occlusions and smiling faces.

- Computational time is less than 1 second for a set of 80 images.

- This method can be combined with supervised approaches to enhance the accuracy of existing facial expression detection algorithms.

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