Ubiquitous Computing Laboratory
Kyung Hee University, Korea

PhD Dissertation Presentation

Accurate and Robust Methodology for Pose and Spontaneous based Facial Expression Recognition

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Introduction

Facial Expression Recognition (FER)

In our daily conversation, FER has 55% contribution [1].

Pose-based FER [2,3]

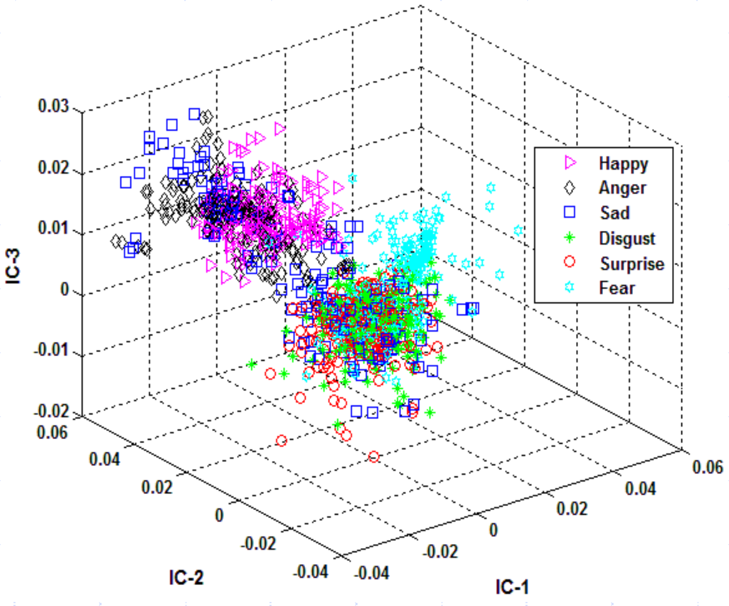
Artificially made by the subjects, i.e., they are forced to perform [4]

Spontaneous-based FER [5,6]

observed on a day-to-day basis, e.g., during conversations or while watching TV [4]

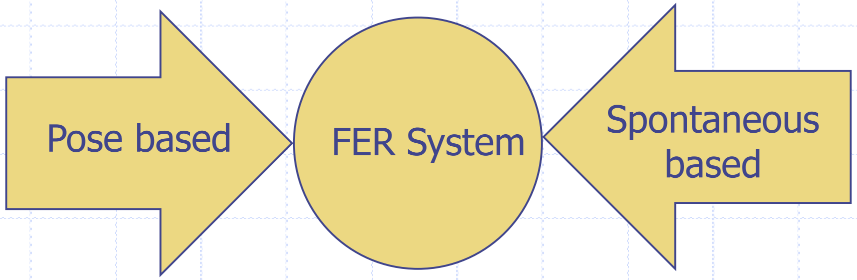
Motivation

- The features mentioned in the figure are highly merged due to similarity among the expressions that results in high within-class variance and low between-class variance



3D-feature plot for six different types of facial expressions.

- Therefore, a system is required
  - to capable of handling posed and spontaneous FER issues
  - to incorporate more intelligent capabilities to transform experimental prototypes into actual usable applications.
  - to identify and characterize some of the most relevant limitations in the FER



Problem Statement

- How do we accurately and robustly recognize facial expressions in complex environments?
  - How do we extract and select the best features from the contributing parts of the face?
  - To what extend is the FER methodology able to predict the label of the facial expressions in dynamic environments?

Goals

- To design, implement, and evaluate an accurate and robust methodology for pose and spontaneous based FER, which has the following objectives
  - reduce classes similarities, accurate face detection, best features extraction and selection, complex distribution-based recognition in naturalistic environment

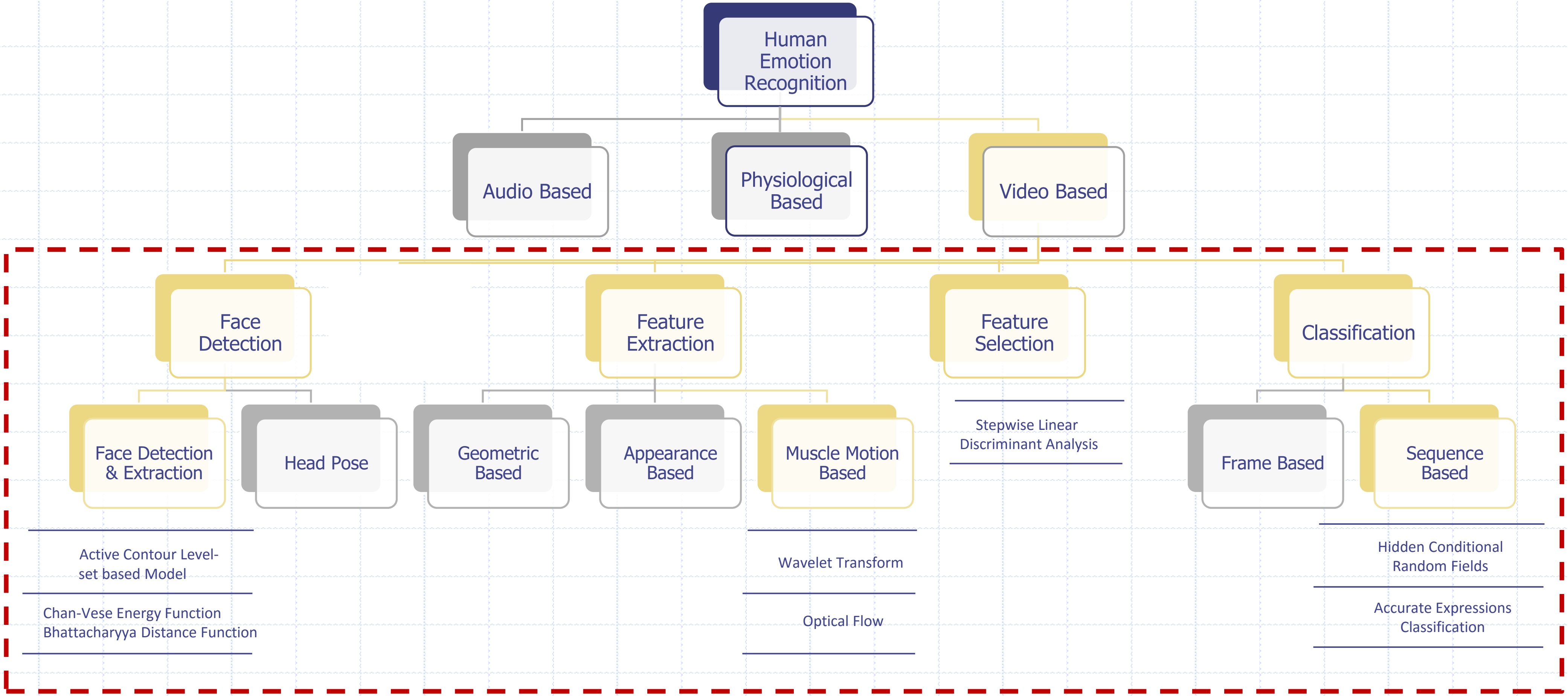
Challenges

To minimize and maximize the variances within and between the classes

To maintain higher accuracy in pose and spontaneous FER domains

Robustness of the system against different domains

Research Taxonomy



Related Work and their Limitations

FER System Modules	Methods	Datasets	Accuracy	Limitations
Face Detection	Appearance-based [7-10] Feature-based methods [11-15], Geometric-based methods [16-18], Knowledge-based methods [19-21], Skin tone-based methods [22-25], and Template-based methods [26].	Yale B FEI CK CK+ AT&T	80-91%	The performance of appearance-based methods degrades with the environmental change [27]. A prior knowledge is required for these methods, i.e., at the time of implementation for these techniques, it is compulsory to decide randomly which intensity information will be important [28]. The performance of geometric-based approaches degrades with the variation in lighting conditions and viewpoint [29]. For knowledge-based approaches it is very hard for these approaches to build an appropriate set of rules. If the rules are too general then there could be several false positives, or there could be false negatives if the rules are in too detail [30]. Skin tine-based methods are very sensitive to illumination like under varying lighting conditions [31]. Template-based methods are very sensitive to pixel misalignment in sub-image areas and depends on facial component detection [32].
Feature Extraction	Some holistic methods such as Nearest Features Line-based Subspace Analysis [33], Eigenfaces and Eigenvector [34], [35] and [36], Fisherfaces [37], global features [38], Independent Component Analysis (ICA) [39, 40], Principal Component Analysis (PCA) [41-43], frequency-based methods [44], Gabor wavelet [45]. Some local feature-based methods such as Local Feature Analysis (LFA) [48], Gabor features [49], Non-negative Matrix Factorization (NMF) and Local non-negative Matrix Factorization (LNMF) [50], and Local Binary Pattern (LBP) [51, 52], Local Transitional Pattern (LTP) [53], Local Directional Pattern (LDP) [54].	CK JAFFE MMI CMU-PIE Yale B+ USTC-NVIE FEI CK+	77-85% 72-92%	Holistic methods are very sensitive to variations in pose, illumination, occlusion, aging, and rotation changes of the face [46], [47]. The performance of local feature-based methods degrade in non-monotonic illumination change, noise variation, change in pose, and expression conditions [28].
Feature Selection	Principal Component Analysis (PCA) [56], Linear Discriminant Analysis (LDA) [58], Kernel Discriminant Analysis (KDA) [60], Generalized Discriminant Analysis (GDA) [62]	CK JAFFE CK CK	83-87%	PCA has poor discriminating power [57]. LDA-based methods suffer from the limitations that their optimality criteria are not directly associated to the classification capability of the achieved feature representation [59]. KDA does not have the capability to provide better performance in the case if the face images of the same subjects are scattered rather than dispersed as clusters [61]. GDA might not be stable and perhaps is not optimal in terms of the discriminant ability if there is small sample size data in the training data [63].

Related Work and their Limitations

FER System Module	Methods	Accuracy
Face Detection	Appearance-based [7-10], Skin tone-based methods [11-14], and Template-based methods [15]	80-91%

Limitations
- The performance of appearance-based methods degrades with the environmental change [21]
- Skin tine and template based methods are very sensitive to illumination [22] and to pixel misalignment in sub-image areas [23] respectively

FER System Module	Methods	Accuracy
Feature Extraction	Gabor wavelet [16], Local Binary Pattern [17,18], Local Transitional Pattern [19], Local Directional Pattern [20]	72-92%

Limitations
- The performance of these methods degrade during illumination change, noise variation, change in pose, occlusion, and expression conditions [21]

FER System Module	Methods	Accuracy
Feature Selection	Linear Discriminant Analysis [24], Kernel Discriminant Analysis, Generalized Discriminant Analysis [25]	84-87%

Limitations
- The optimality criteria of LDA is not directly associated to the classification capability of the achieved feature representation [28]
- If there is small sample size data in the training data, GDA is not optimal in terms of the discriminant [29]

FER System Module	Methods	Accuracy
Classification	Support vector machine [26], hidden Markov model [27]	85-90%

Limitations
- SVM has no direct estimation of the probability [30]
- HMMs presume that the current state depends only on the previous state. Because of this assumption, labels of two contiguous states must hypothetically occur consecutively in the observed sequence. However, this presumption is not always true in reality

Related Work and their Limitations

$$p(Y \mid X;\Lambda) = \frac{\sum_{\bar{S}} \exp\left\{\Lambda \cdot f\left(Y,\bar{S},X\right)\right\}}{z\left(X,\Lambda\right)}$$

$$f_{y'}^{Pr}\left(Y,\bar{S},X\right) = \delta\left(y_1 = y'\right), \quad \forall y' \in Y,$$

$$f_{ss'}^{Tr}\left(Y,\bar{S},X\right) = \sum_{t=1}^{T} \delta\left(s_{t-1} = s\right)\delta\left(s_t = s'\right), \quad \forall \{ss'\} \in \bar{S},$$

$$f_{s}^{Occ}\left(Y,\bar{S},X\right) = \sum_{t=1}^{T} \delta\left(s_t = s\right), \quad \forall s \in \bar{S},$$

$$f_{s}^{M_1}\left(Y,\bar{S},X\right) = \sum_{t=1}^{T} \delta\left(s_t = s\right) x_t, \quad \forall s \in \bar{S},$$

$$f_{s}^{M_2}\left(Y,\bar{S},X\right) = \sum_{t=1}^{T} \delta\left(s_t = s\right) x_t^2, \quad \forall s \in \bar{S},$$

$$\Lambda_{y'}^{Pr} = \log\left(u_{y'}\right), \quad \forall y' \in Y,$$

$$\Lambda_{ss'}^{Tr} = \log\left(A_{ss'}\right) \quad \forall \{ss'\} \in \bar{S},$$

$$\Lambda_{s}^{Occ} = -\frac{1}{2}\left(\log\left(2\pi\sigma_s^2\right) + \frac{\mu_s^2}{\sigma_s^2}\right),$$

$$\Lambda_{s}^{M_1} = \frac{\mu_s}{\sigma_s^2},$$

$$\Lambda_{s}^{M_2} = -\frac{1}{2\sigma_s^2},$$

$$\sum_{\bar{S}} \exp\left\{\Lambda \cdot f\left(Y,\bar{S},X\right)\right\} = \sum_{\bar{S}} u(s_1) \prod_{t=1}^{T} A\left(s_{t-1}, s_t\right) N(x_t^2, \mu_{s_t}, \sigma_{s_t})$$

$$p(Y \mid X;\Lambda) = \frac{\sum_{\bar{S}} \sum_{m=1}^{M} \exp\left\{\Lambda \cdot f\left(Y,\bar{S},m,X\right)\right\}}{z\left(X,\Lambda\right)}$$

- These equations imply that with a particular set of values, the observation density at each state will converge to Gaussian form. Unfortunately, there is an algorithm that could guarantee this conversion. Therefore, these assumptions may result in a decrease of accuracy

Proposed Methodology

Methodology
FER System

Method-1
Hierarchical Recognition Scheme

Pros:
- Hierarchical recognition scheme
- Recognizing accurate expressions

Cons:
- Two level classification
- Raise complexity issue

Method-2
Robust FER System

Pros:
- Accurate face detection
- Pixel motion-based feature extraction
- Proposed the Improved version of HCRF

Cons:
- Used pose-based datasets

Core Method

Method-3
Spontaneous -based FER

Pros:
- Defined new, innovative, and naturalistic dataset
- Dataset collected from YouTube, real-world talk shows, interviews, speeches, news, and real world incidents

Supporting Methods

Method 1: Hierarchical Recognition Scheme

- This system was based on the theory that different expressions can be grouped into three categories based on the parts of the face that contribute most toward the expression as shown in the table

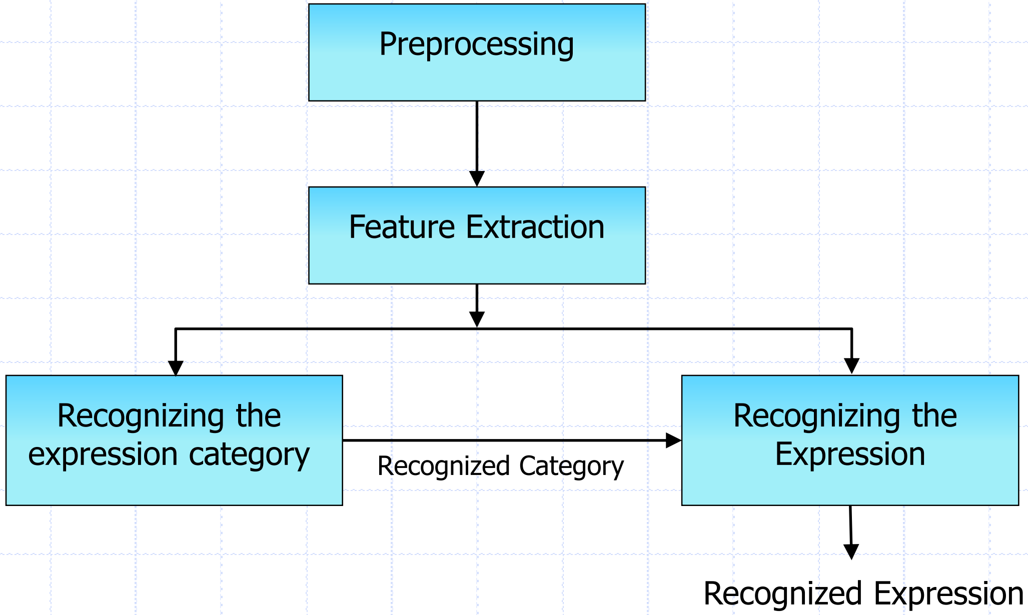
Category	Facial Expressions
Lips-Based	Happy
	Sad
Lips-Eyes-Based	Surprise
	Disgust
Lips-Eyes-Forehead-Based	Anger
	Fear

The classified categories and facial expressions recognized in the proposed hierarchical recognition scheme

- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Method 1: Hierarchical Recognition Scheme

- Overall architecture of the proposed hierarchical recognition scheme is given as



Architectural diagram for the proposed hierarchical recognition scheme

- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Method 1: Hierarchical Recognition Scheme

Recognizing the Expression Category

- At the first level, LDA was applied to the features, and the resulting LDA-features were fed to an HMM to recognize the category for the given expression: lips-based, lips-eyes-based, or lips-eyes-forehead-based expressions

Expression Category
Lips-Based
Lips-Eyes-Based
Lips-Eyes-Forehead-Based

Recognition of the expression-categories at the first level

Recognizing the Expressions

- Once the category of the given expression has been determined, the label for the expression within the recognized category is recognized at the second level by again feeding the features to a combination of LDA and HMM

Facial Expressions
Happy
Sad
Surprise
Disgust
Anger
Fear

Recognition of expressions in the recognized category at the second level

- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Method 1: Experimental Setup

For a thorough validation, the following experiments were performed in Matlab using an Intel↓ Pentium↓ Dual-Core™ (2.5 GHz) with a RAM capacity of 3 GB

Hierarchical Recognition Scheme

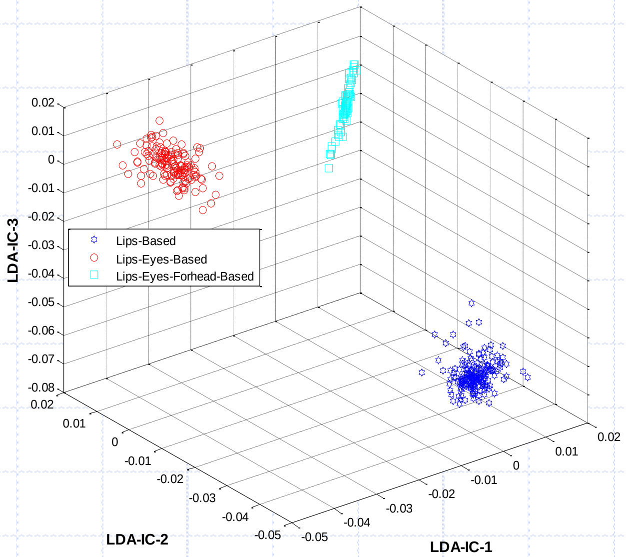
- Using 10-fold cross validation rule for the system on two datasets
  - Cohn-Kanade Dataset
  - JAFFE Dataset
- Accuracy under the absence of hierarchical scheme

- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

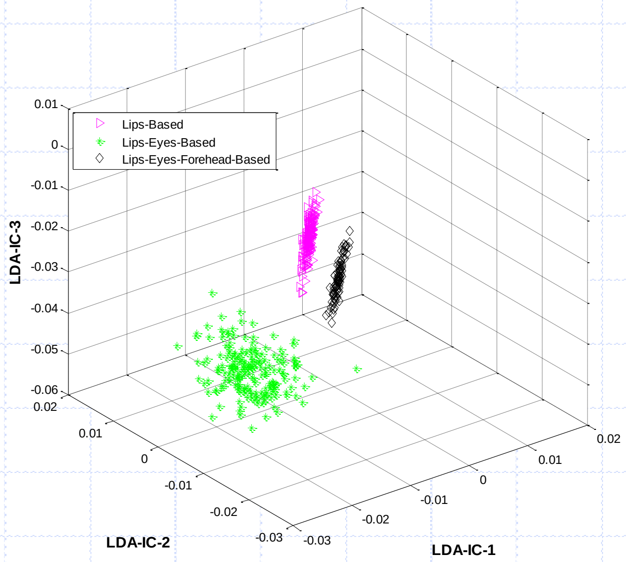
Method 1: Experimental Results – Hierarchical Scheme

First Experiment: Results of the Hierarchical Scheme

- Recognizing the Expression Category
  - At the first level, LDA was applied to the features, and the resulting LDA-features were fed to an HMM to recognize the category for the given expression



3D feature plots for the three expression-categories at the first level using Cohn-Kanade dataset

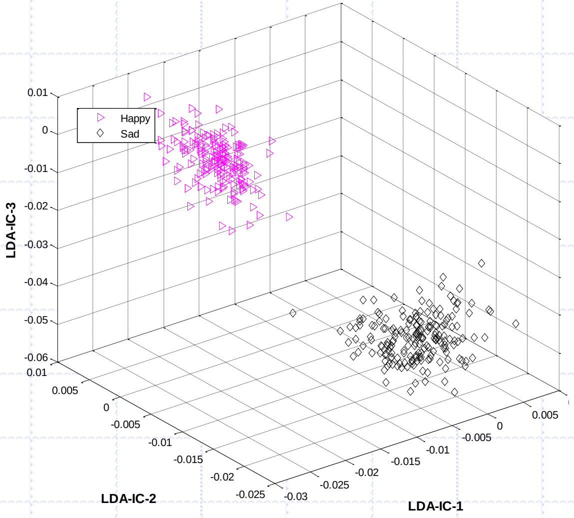


3D feature plots for the three expression-categories at the first level using JAFFE dataset

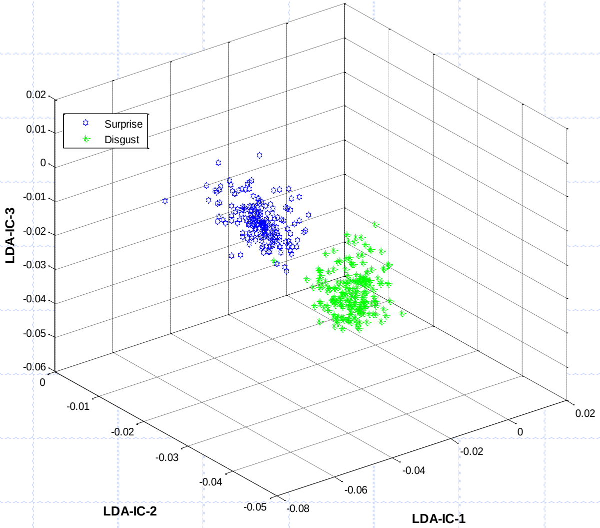
- ***Siddiqi, et. al***., “Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems”, Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Method 1: Experimental Results – Hierarchical Scheme

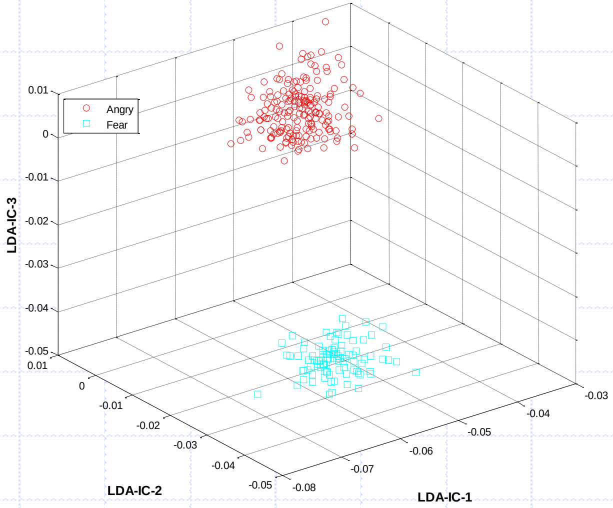
- First Experiment: Results of the Hierarchical Scheme
  - Recognizing the Expressions
    - Once the category of the given expression has been determined, the label for the expression within the recognized category is recognized at the second level



LDA-features space for lips-based category



LDA-features space for lips-eyes-based category

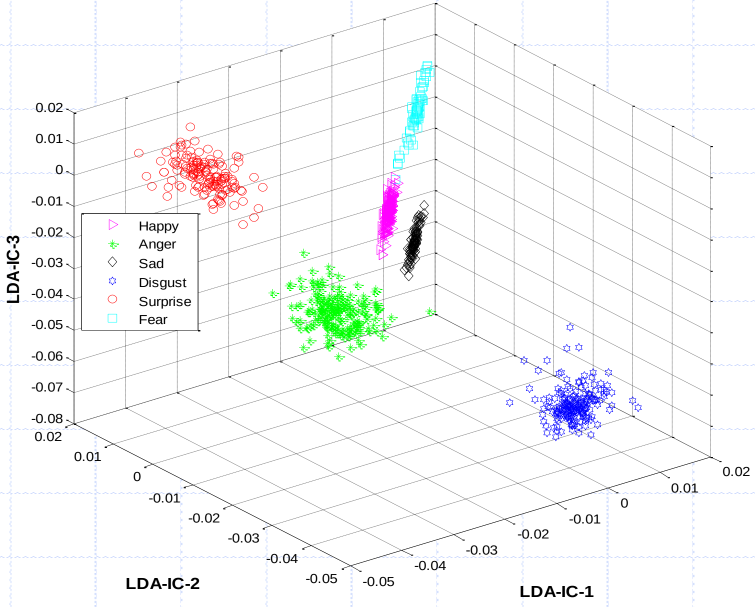


LDA-features space for lips-eyes-forehead-based category

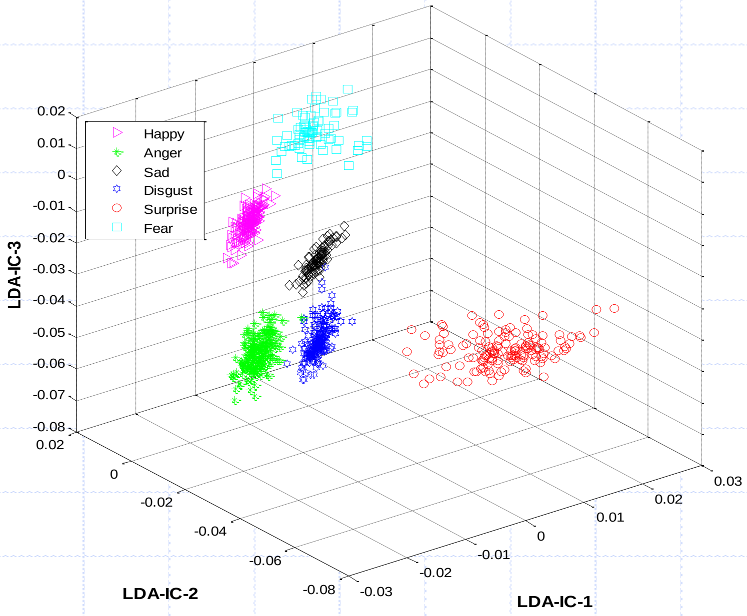
- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Method 1: Experimental Results – Hierarchical Scheme

- First Experiment: Results of the Hierarchical Scheme



Classification results of the proposed scheme on Cohn-Kanade dataset (97.87%)

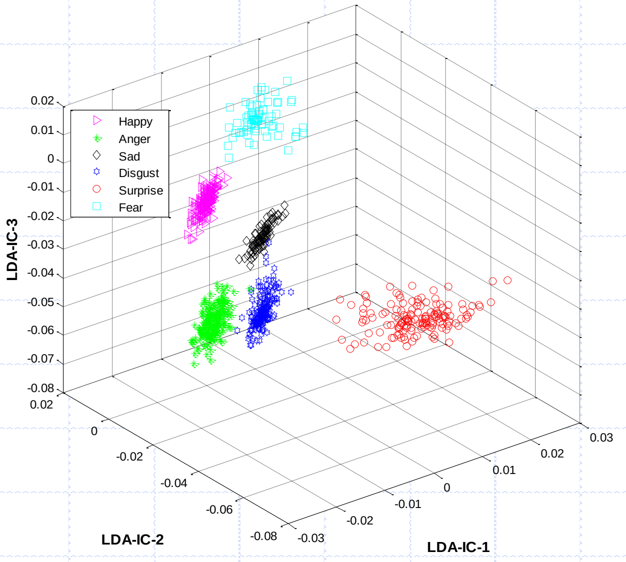


Classification results of the proposed scheme on JAFFE dataset (98.83%)

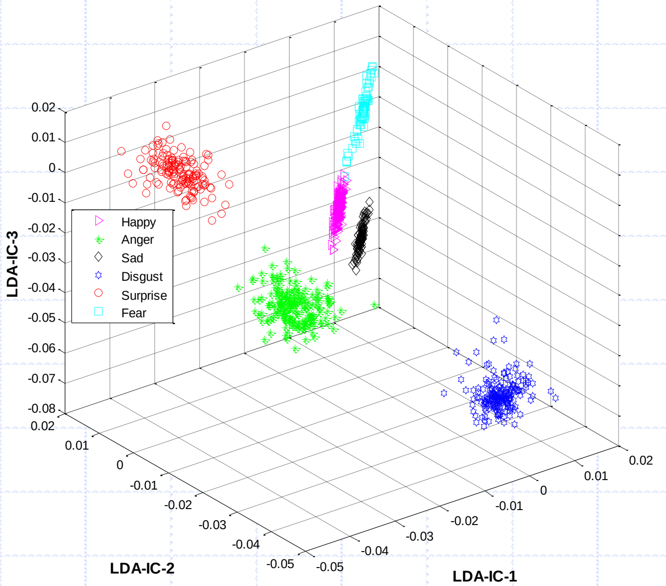
- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Method 1: Experimental Results – Hierarchical Scheme

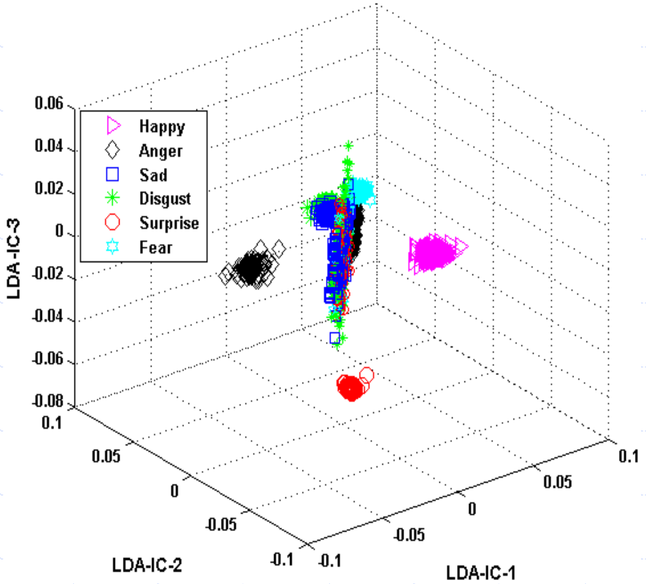
- Second Experiment: Results of the System under the Absence of Hierarchical Scheme



Classification results of the proposed scheme on JAFFE dataset (98.83%)



Classification results of the proposed scheme on Cohn-Kanade dataset (97.87%)



Classification results under the absence of the proposed hierarchical scheme (89.8%)

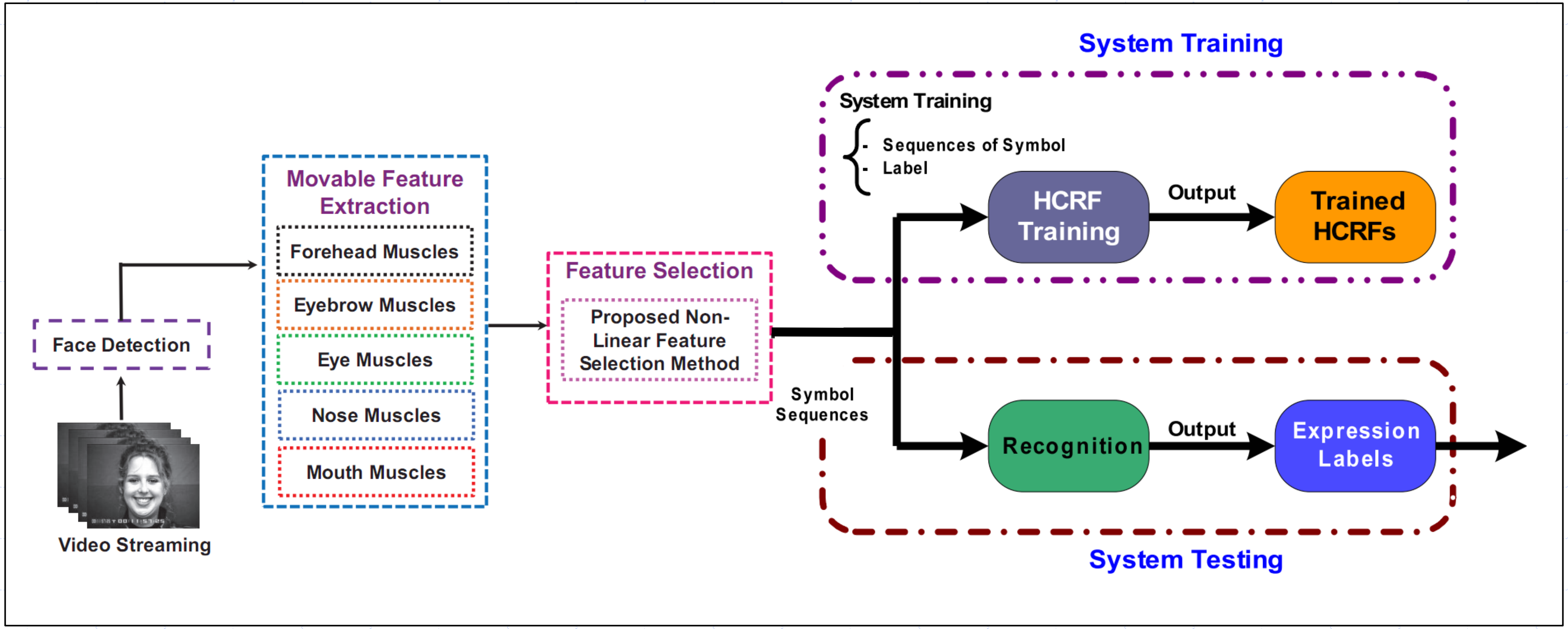
- ***Siddiqi, et. al***., "Hierarchical Recognition Scheme for Human Facial Expression Recognition Systems", Sensors (SCIE, IF: 2.245), vol. 13, no. 12, pp. 16682 – 16713, 2013

Limitation of Method 1

- The proposed hierarchical recognition scheme showed better performance and achieved high recognition rate
- However, in this scheme, two-level-recognition with LDA and HMMs used at each level
- Due to this multilevel classification, the proposed work may raise complexity issue

Method 2: Robust FER System

- Overall architectural diagram of the proposed FER system



Architectural diagram for the proposed FER system

- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014
- ***Siddiqi, et. al***., "Human Facial Expression Recognition using Stepwise Linear Discriminant Analysis and Hidden Conditional Random Fields", IEEE Transactions on Image Processing (SCI, IF: 3.625), vol. 24, no. 4, pp. 1386 – 1398, 2015

Method 2: Proposed Face Detection and Extraction Method

- A convex combination of two energy functions *F(C)* and *B(C)*

$$E_0(C) = \beta F(C) + (1-\beta)B(C)$$

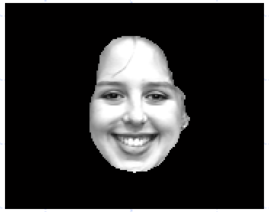
β - weights the constraints of within-face homogeneity and between-face dissimilarity $\beta = 0.2$

- More robust to noise and illumination changes

$$B(C) = \int_z \sqrt{p_{in}(z)\, p_{out}(z)}\, dx$$

$$\mathrm{p_{in}}(\mathrm{z}) = \frac{\int_\Omega \delta(\mathrm{z} - \mathrm{I}(\mathrm{x}))\,\mathrm{H}(-\phi(\mathrm{x}))\,\mathrm{dx}}{\int_\Omega \mathrm{H}(-\phi(\mathrm{x}))\,\mathrm{dx}}$$

$$\mathrm{p_{out}}(\mathrm{z}) = \frac{\int_\Omega \delta(\mathrm{z} - \mathrm{I}(\mathrm{x}))\,\mathrm{H}(\phi(\mathrm{x}))\,\mathrm{dx}}{\int_\Omega \mathrm{H}(\phi(\mathrm{x}))\,\mathrm{dx}}$$



$$\frac{\partial \phi}{\partial t} = \left\{ \begin{array}{l} \gamma + \eta + \beta\left[(I - c_{in})^2 + (I - c_{out})^2\right] \\ -(1-\beta)\left[\frac{B(C)}{2}\left(\frac{1}{A_{in}} - \frac{1}{A_{out}}\right) + \frac{1}{2}\int_z \delta(z-1)\left(\frac{1}{A_{out}}\sqrt{\frac{p_{in}}{p_{out}}} - \frac{1}{A_{in}}\sqrt{\frac{p_{out}}{p_{in}}}\right) dz\right] \end{array} \right\}$$

γ - helps to detect objects of various sizes, including small points caused by noise and $\gamma = 0.5$

η - speeds up the function evolution and $\eta = 0.000001$

- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Proposed Feature Extraction Method

$$X = A_1 + D_1$$

$$X = A_j + D_j + D_{j-1} + D_{j-2} + \ldots\ldots + D_2 + D_1$$

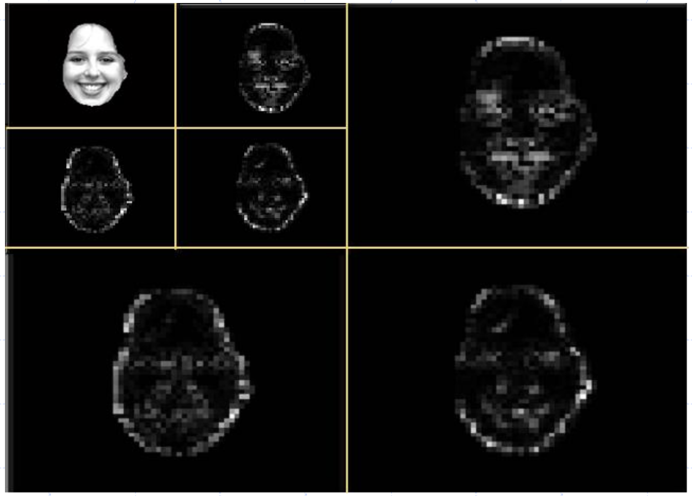
$$X = A_2 + D_2 + D_1$$

$$= A_2 + \left[(D_h)_2 + (D_v)_2 + (D_d)_2\right] + \left[(D_h)_1 + (D_v)_1 + (D_d)_1\right]$$

$$X = A_2 + \sum_{i=2}^{1}\left[(D_h)_i + (D_v)_i + (D_d)_i\right]$$

$$C(a_i, b_j) = \frac{1}{\sqrt{a_i}} \int_{-\infty}^{\infty} y(t)\,\psi^*_{f.e}\left(\frac{t - b_j}{a_i}\right) dt$$

$$f_m = \frac{f_a(\psi_{f.e})}{a_m(\psi_{f.e}).\Delta}$$



- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Proposed Feature Extraction Method

$$g_x(i,j) = \frac{j-k-1}{2\pi\Sigma^3}\exp\left(\frac{(i-k-1)^2+(j-k-1)^2}{2\Sigma^2}\right)$$

$$g_y(i,j) = \frac{j-k-1}{2\pi\Sigma^3}\exp\left(-\frac{(i-k-1)^2+(j-k-1)^2}{2\Sigma^2}\right)$$

$$\mathrm{kernel}(i,j) = -\frac{1}{2\pi\sigma^2}\exp\left(-\frac{(i-k-1)^2+(j-k-1)^2}{2\sigma^2}\right)$$

$$A = \begin{bmatrix} \Sigma I_x, I_x & \Sigma I_x, I_y \\ \Sigma I_y, I_x & \Sigma I_y, I_y \end{bmatrix} \quad B = \begin{bmatrix} \Sigma I_x, I_t \\ \Sigma I_y, I_t \end{bmatrix} \quad R = A^{-1}(-B)$$

$$f_{ave} = \frac{R_1 + R_2 + R_3 +, \ldots\ldots, + R_K}{N}$$

- We utilized a robust method like Stepwise Linear Discriminant Analysis (SWLDA) [31] in order to select a set of best features from the entire features

- ***Siddiqi, et. al***., “Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection”, Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Proposed Recognition Model

$$f_{y'}^{Pr}\left(Y,\bar{S},X\right)=\delta\left(y_1=y'\right),\quad \forall y'\in Y,$$

$$f_{ss'}^{Tr}\left(Y,\bar{S},X\right)=\sum_{t=1}^{T}\delta\left(s_{t-1}=s\right)\delta\left(s_t=s'\right),\quad \forall\{ss'\}\in\bar{S},$$

$$f_{s}^{Ob}\left(Y,\bar{S},X\right)=\sum_{t=1}^{T}\log\left(\sum_{m=1}^{M}\Gamma_{s,m}^{Obs}N\left(x_t^2,\mu_{s,m},\Sigma_{s,m}\right)\right)\delta\left(s_t=s\right),$$

$$N\left(x_t^2,\mu_{s,m},\Sigma_{s,m}\right)=\frac{1}{\left(2\pi\right)^{D/2}\left|\Sigma_{s,m}\right|^{1/2}}\exp\left(-\tfrac{1}{2}\left(x_t^2-\mu_{s,m}\right)'.\Sigma_{s,m}^{-1}(x_t^2-\mu_{s,m})\right),$$

$$p\left(Y\mid X;\Lambda,\Gamma,\mu,\Sigma\right)=\frac{\sum_{\bar{S}}\exp\left(\sum_{s}\Lambda_s^{Pr}f_s^{Pr}\left(Y,\bar{S},X\right)+\sum_{ss'}\Lambda_{ss'}^{Tr}f_{ss'}^{Tr}\left(Y,\bar{S},X\right)+\sum_{s}f_s^{Ob}\left(Y,\bar{S},X\right)\right)}{z\left(X,\Lambda,\Gamma,\mu,\Sigma\right)},$$

$$p\left(Y\mid X;\Lambda,\Gamma,\mu,\Sigma\right)=\frac{\sum_{\bar{S}=s_1,s_2,..,s_T}\exp\left(\Lambda_{s_1}^{Pr}+\sum_{t=1}^{T}\left(\Lambda_{s_{t-1},s_t}^{Tr}\right)+\log\left(\sum_{m=1}^{M}\Gamma_{s_t,m}^{Obs}N\left(x_t^2,\mu_{s_t,m},\Sigma_{s_t,m}\right)\right)\right)}{z\left(X,\Lambda,\Gamma,\mu,\Sigma\right)}$$

- ***Siddiqi, et. al***., "Human Facial Expression Recognition using Stepwise Linear Discriminant Analysis and Hidden Conditional Random Fields", IEEE Transactions on Image Processing (SCI, IF: 3.625), vol. 24, no. 4, pp. 1386 – 1398, 2015

Method 2: Proposed Recognition Model

$$p\left(Y \mid X;\Lambda,\Gamma,\mu,\Sigma\right)=\frac{Score\left(Y \mid X;\Lambda,\Gamma,\mu,\Sigma\right)}{z\left(X,\Lambda,\Gamma,\mu,\Sigma\right)}$$

$$\alpha_\tau=\sum_{\bar{S}=s_1,s_2,\ldots,\{s_\tau=s\}}\exp\left(\Lambda_{s_1}^{Pr}+\sum_{t=1}^{T}\left(\Lambda_{s_{t-1},s_t}^{Tr}\right)+\log\left(\sum_{m=1}^{M}\Gamma_{s_t,m}^{Obs}N.\left(x_t^2,\mu_{s_t,m},\Sigma_{s_t,m}\right)\right)\right)$$

$$=\sum_{s'}\alpha_{\tau-1}\left(s'\right)\exp\left(\Lambda_{ss'}^{Tr}+\log\left(\sum_{m=1}^{M}\Gamma_{s_t,m}^{Obs}N.\left(x_\tau,\mu_{s,m},\Sigma_{s,m}\right)\right)\right),$$

$$\beta_\tau\left(s\right)=\sum_{\bar{S}=\{s_\tau=s\},s_{\tau+1},\ldots,s_T}\exp\left(\Lambda_{s_1}^{Pr}+\sum_{t=1}^{T}\left(\Lambda_{s_{t-1},s_t}^{Tr}\right)+\log\left(\sum_{m=1}^{M}\Gamma_{s_t,m}^{Obs}N\cdot\left(x_t^2,\mu_{s_t,m},\Sigma_{s_t,m}\right)\right)\right)$$

$$=\sum_{s'}\beta_{\tau+1}\left(s'\right)\exp\left(\Lambda_{ss'}^{Tr}+\log\left(\sum_{m=1}^{M}\Gamma_{s,m}^{Obs}N\cdot\left(x_\tau,\mu_{s,m},\Sigma_{s,m}\right)\right)\right),$$

- ***Siddiqi, et. al***., "Human Facial Expression Recognition using Stepwise Linear Discriminant Analysis and Hidden Conditional Random Fields", IEEE Transactions on Image Processing (SCI, IF: 3.625), vol. 24, no. 4, pp. 1386 – 1398, 2015

Method 2: Experimental Setup

For a thorough validation, the following experiments were performed in Matlab using an Intel® Pentium® Dual-Core™ (2.5 GHz) with a RAM capacity of 3 GB

Robust FER System

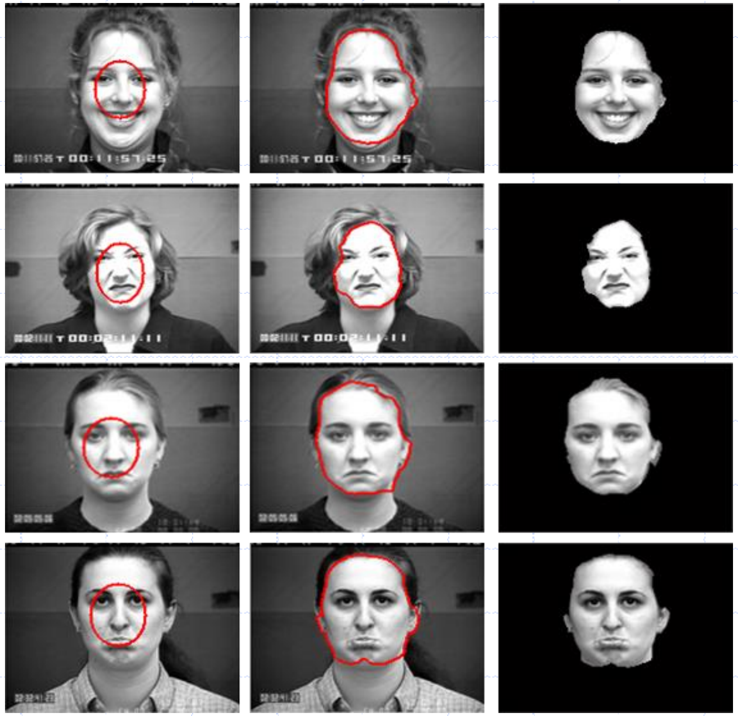
- Face detection and extraction on CK+ dataset
- 10-fold cross validation rule for the system on four datasets
  - Extended Cohn-Kanade (CK+) Dataset
  - USTC-NVIE (Posed) Dataset
  - MUG Dataset
  - MMI Dataset
- Robustness using *n*-fold cross validation rule (where, *n*=4)
- Accuracy under the absence of each module
- Comparison against existing systems
  - State-of-the-art Systems (8)

- ***Siddiqi, et. al***., "Human Facial Expression Recognition using Stepwise Linear Discriminant Analysis and Hidden Conditional Random Fields", IEEE Transactions on Image Processing (SCI, IF: 3.625), vol. 24, no. 4, pp. 1386 – 1398, 2015
- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Face Detection

- First Experiment: Face Detection and Extraction using Extended Cohn-Kanade (CK+) Dataset

Face Extraction by existing work

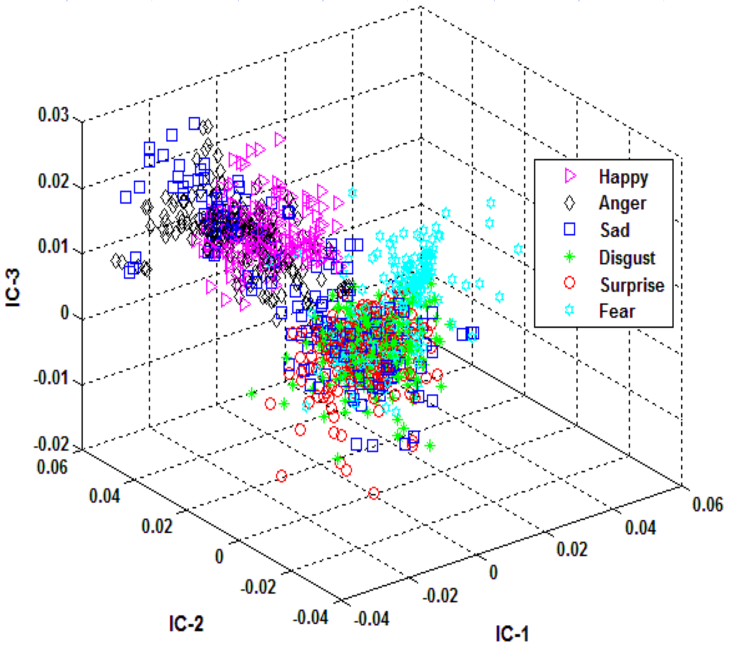


Face Extraction by the proposed technique

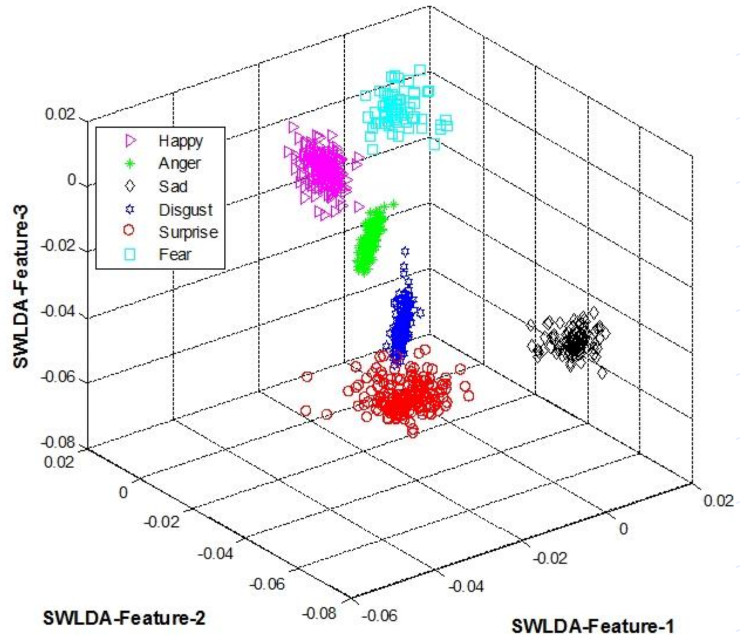
- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

- Second Experiment: Using Extended Cohn-Kanade (CK+) Dataset



3D-feature plot for six different types of facial expressions

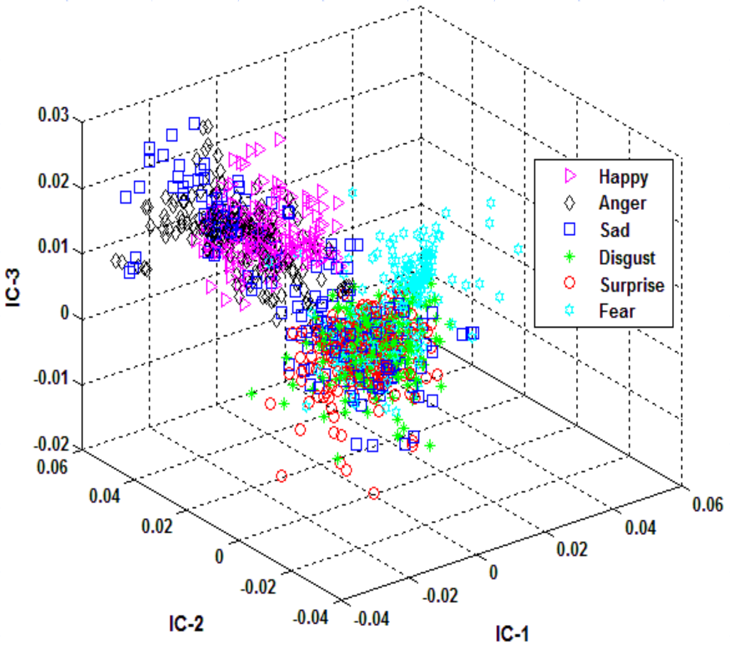


3D-feature plot of the technique on CK+ dataset (97%)

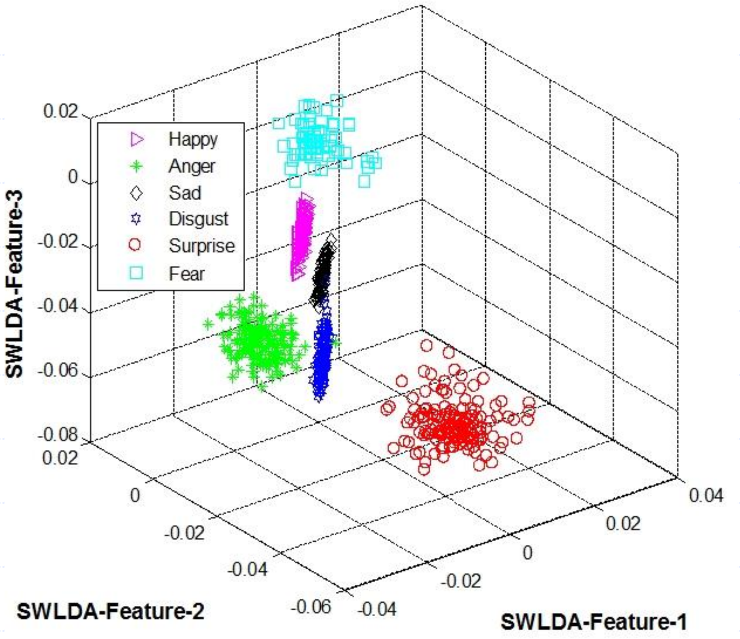
- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

◆ Second Experiment: Using USTC-NVIE Dataset



3D-feature plot for six different types of facial expressions

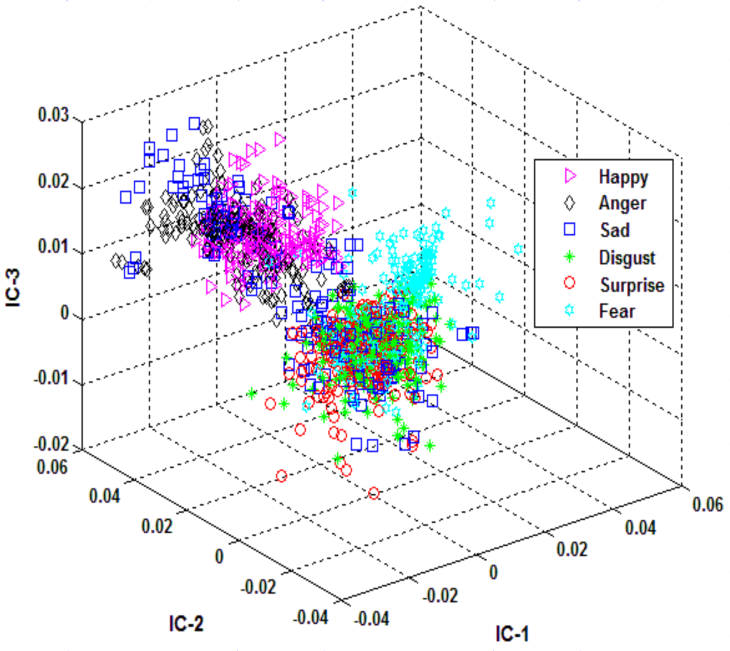


3D-feature plot of the technique on USTC-NVIE dataset (97.16%)

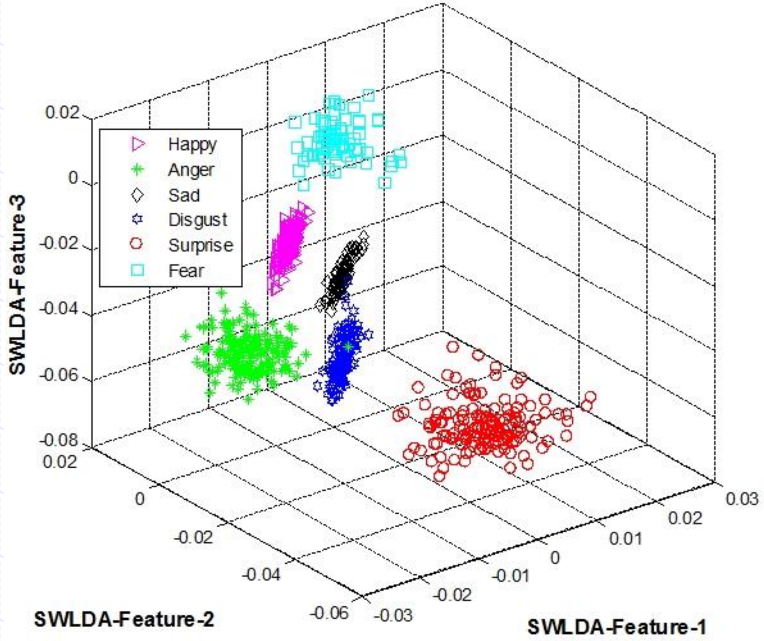
- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

- Second Experiment: Using Multimedia Understanding Group (MUG) Dataset



3D-feature plot for six different types of facial expressions

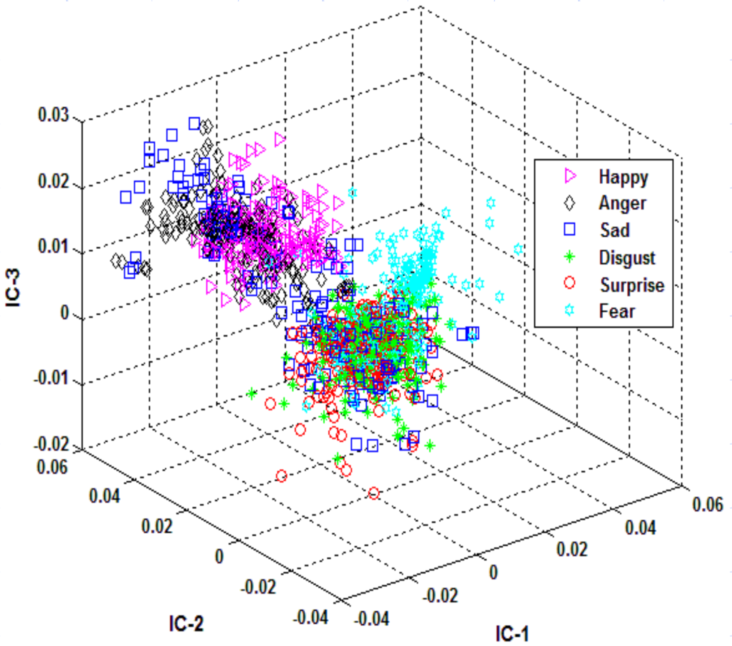


3D-feature plot of the technique on MUG dataset (97.00%)

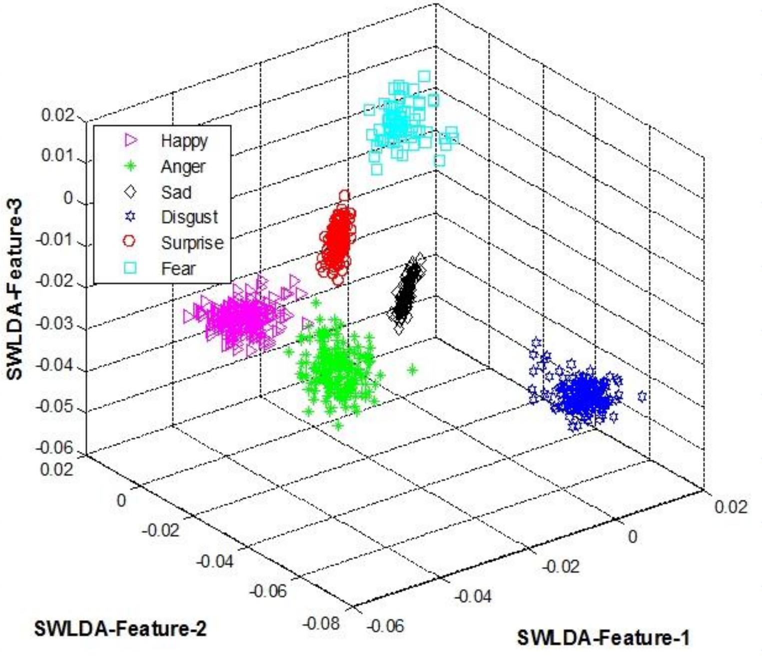
- ***Siddiqi, et. al.***, "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

- Second Experiment: Using MMI Dataset



3D-feature plot for six different types of facial expressions

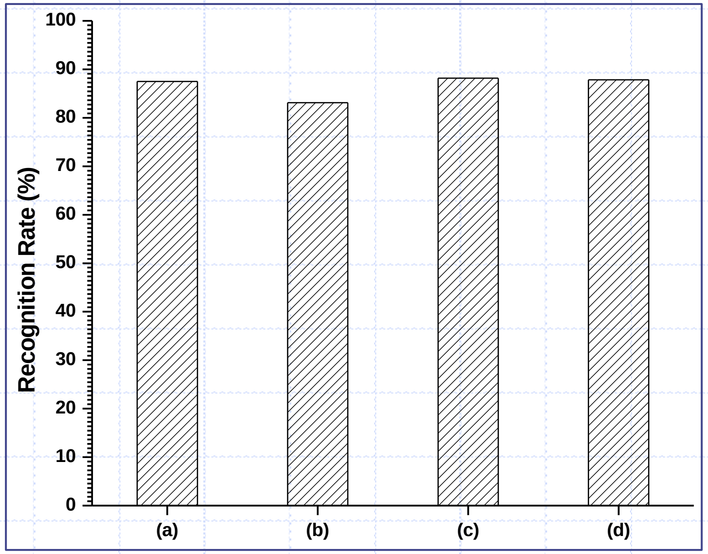


3D-feature plot of the technique on MMI dataset (97.83%)

- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

- Third Experiment: Results of the Proposed Robust FER Methodology (Robustness)

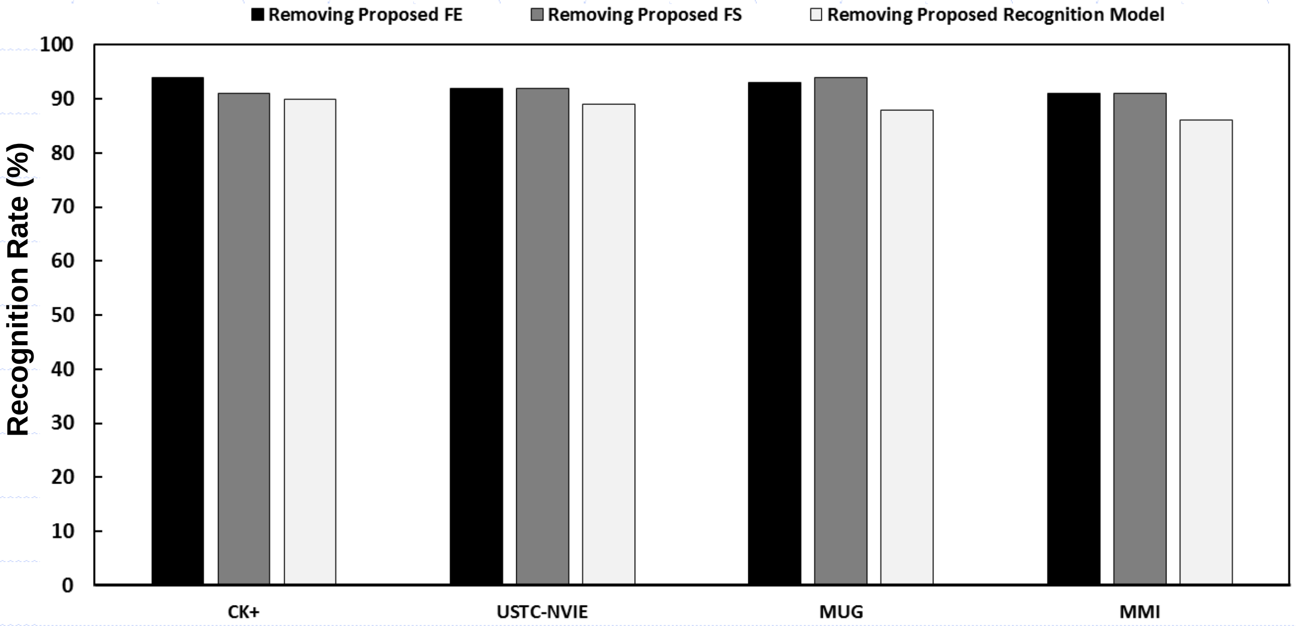


Recognition rate of the proposed approaches (a) training on Extended Cohn–Kanade (CK+) dataset and testing on USTC-NVIE, MUG, and MMI datasets, (b) training on USTC-NVIE dataset and testing on CK+, MUG, and MMI datasets, (c) training on MUG dataset and testing on CK+, USTC-NVIE, and MMI datasets, (d) training on MMI dataset and testing on CK+, USTC-NVIE, and MUG datasets

- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

◆ Fourth Experiment: Results under the Absence of Each Module

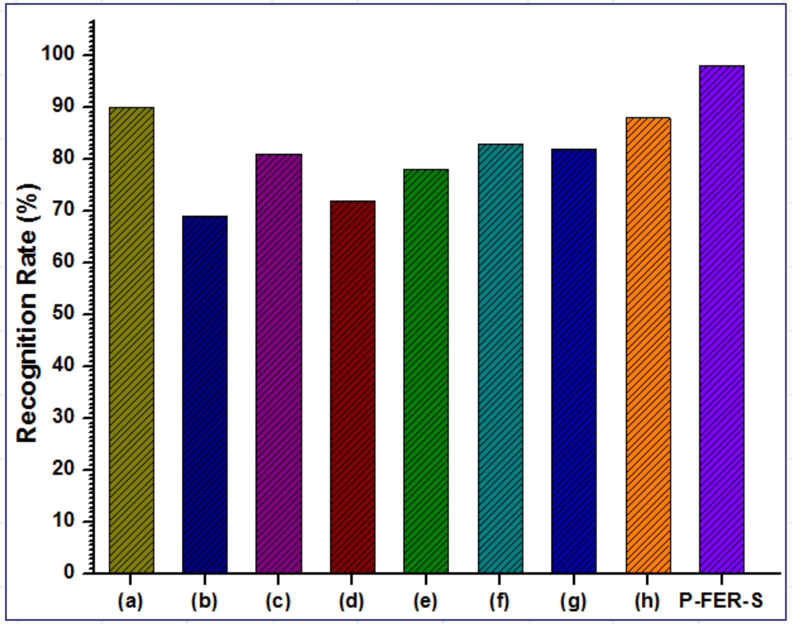


Recognition rates of the proposed system under the absence of individual proposed method (such as proposed feature extraction (FE), feature selection (FS), and recognition model) using all the four datasets in order to show the efficacy of each method

- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Method 2: Experimental Results – Robust FER System

- Fifth Experiment: Comparison against some existing systems



Comparison results of the proposed FER system (P-FER-S) against some state-of-the-art (unit %), where (a) is [32], (b) is[33], (c) is [34], (d) is [35], (e) is [36], (f) is [37], (g) is [38], and (h) is [39]

- ***Siddiqi, et. al***., "Facial Expression Recognition using Active Contour-based Face Detection, Facial Movement-based Feature Extraction, and Non-Linear Feature Selection", Multimedia Systems (SCI, IF: 0.619), vol. 21, no. 6, pp. 541 – 555, 2014

Limitations of Method 2

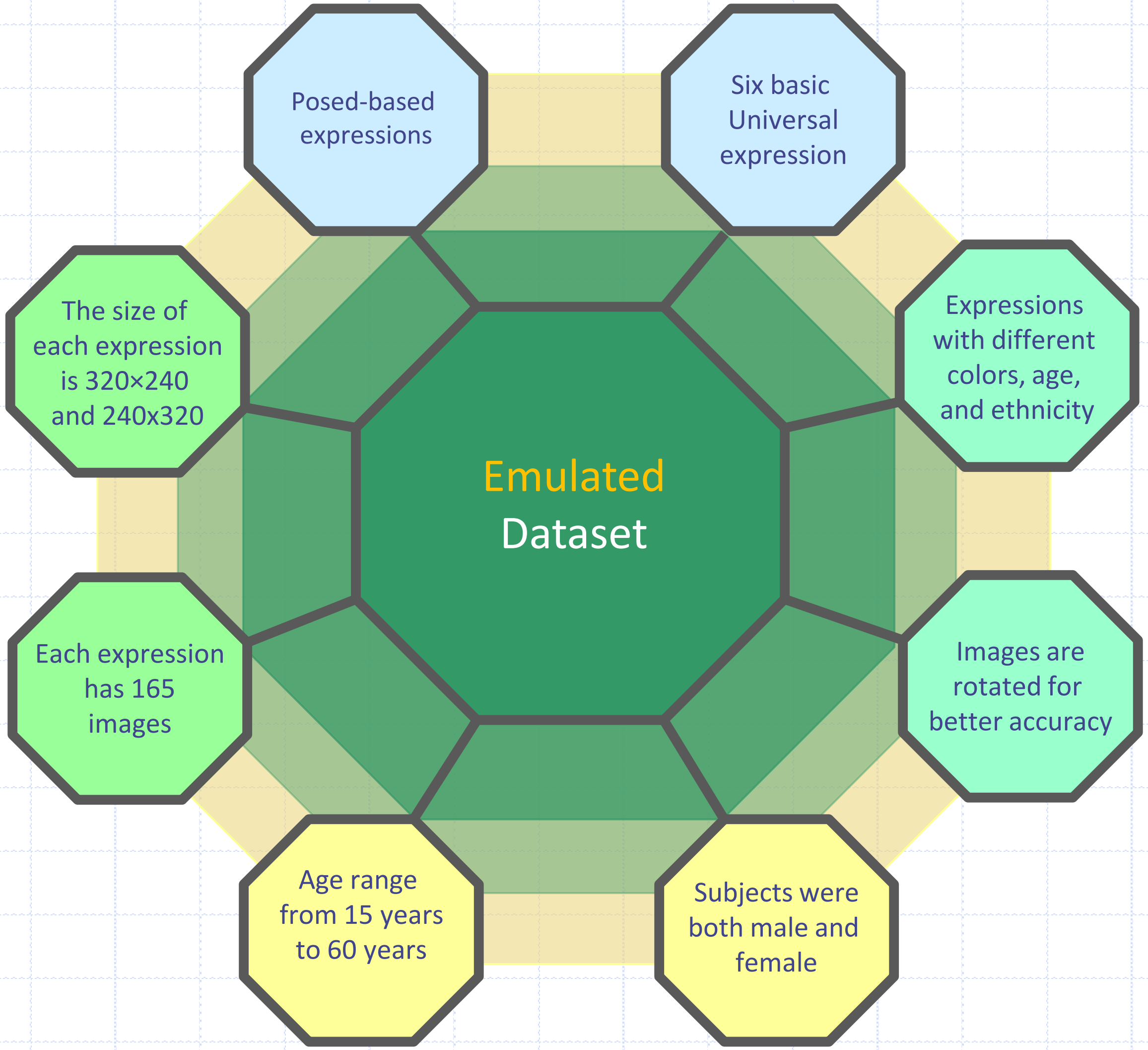
- Most of the previous datasets were collected under controlled environments with predefined setup of camera and light
- They did not consider gender, race, and age like features
- Mostly, the size of the face is constant and the subjects have slight variation with the camera
- The subjects are partially makeup or over-makeup and small faces did not consider
- Most of the spontaneous datasets were collected for the purpose of face recognition and they have minimal number of expressions

Method 3: Defined Naturalistic Dataset

- We have defined a realistic and innovative dataset collected from YouTube, some real world talk shows and interviews, and speeches. From an indoor lab settings to a real-life environment, we defined three cases with increasing complexity
  - Emulated Dataset
  - Semi-naturalistic Dataset
  - Naturalistic Dataset
- In order to make the consistency among the expressions, all the images
  - Captured images from the videos by using GOMPlayer software [36]
  - Resized by using Fotosizer software [37]
- We believe that due to the distinct features of the collected datasets, the standard FER methodologies can be tested and validated in a more rigorous fashion. These datasets will be made available for future research to the research community.

- ***Siddiqi, et. al*.**, "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Systems (SCI, IF: 0.619), 2015 (Under Review)

Method 3: Defined Emulated Dataset



Method 3: Defined Semi-naturalistic Dataset

- Six basic universal Expressions
- Collected from movies and dramas
- No control on light and camera settings
- wearing hat and glasses, hair open and beard
- Each expression has 165 images of size 320×240 and 240x320

Method 3: Defined Naturalistic Dataset

Naturalistic Dataset

- **Six basic expressions**
- **Collected Real world talks shows & incidents**
- **165 images in each expression**
- **Image size 320x240, and 240x320**

Method 3: Defined Dataset

- Sample images for all the dataset are given below

Sample images for the defined dataset, emulated (top), semi-naturalistic (middle), and naturalistic (bottom) datasets, respectively

Method 3: Experimental Setup

For a thorough validation, the following experiments were performed in Matlab using an Intel↓ Pentium↓ Dual-Core™ (2.5 GHz) with a RAM capacity of 3 GB

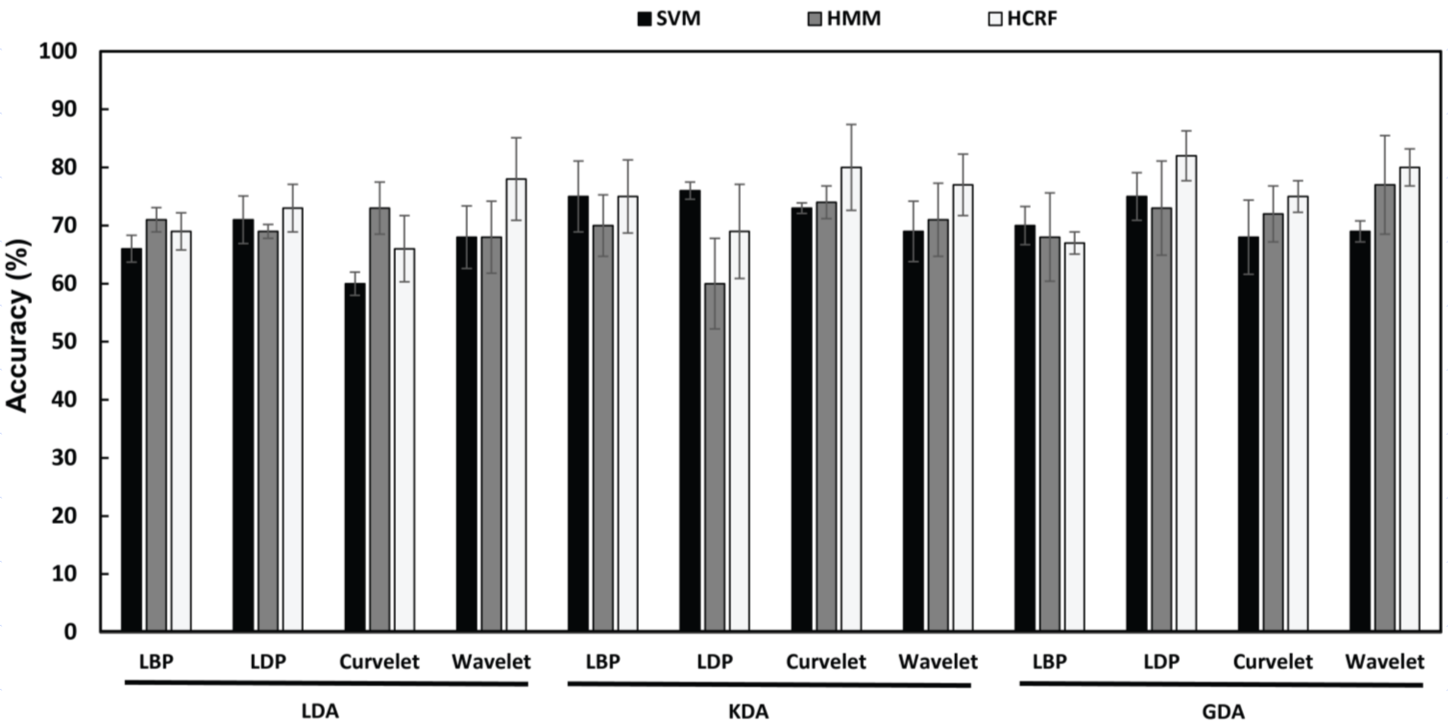
Spontaneous FER System

- 10-fold cross validation rule for the previous standard methodologies on the defined datasets
  - Emulated Dataset
  - Semi-naturalistic Dataset
  - Naturalistic Dataset
- 10-fold cross validation rule for the state-of-the-art using the defined datasets
- 10-fold cross validation rule for the system on previous spontaneous datasets
  - USTC-NVIE (Spontaneous) Dataset
  - IMFDB Dataset
- 10-fold cross validation rule for the system on the defined datasets
- Robustness using *n*-fold cross validation rule (where, *n*=3)
- Accuracy under the absence of each module
- Comparison against existing systems
  - State-of-the-art Systems (8)

- ***Siddiqi, et. al***., "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Systems (SCI, IF: 0.619), 2015 (under review)
- ***Siddiqi, et. al***., "Spontaneous-based Facial Expression Recognition System using Real-time YouTube Dataset", IEEE Transactions on Pattern Analysis and Machine Intelligence (SCI, IF: 5.781), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

- First Experiment: Results of the Standard Methodologies using Emulated Dataset

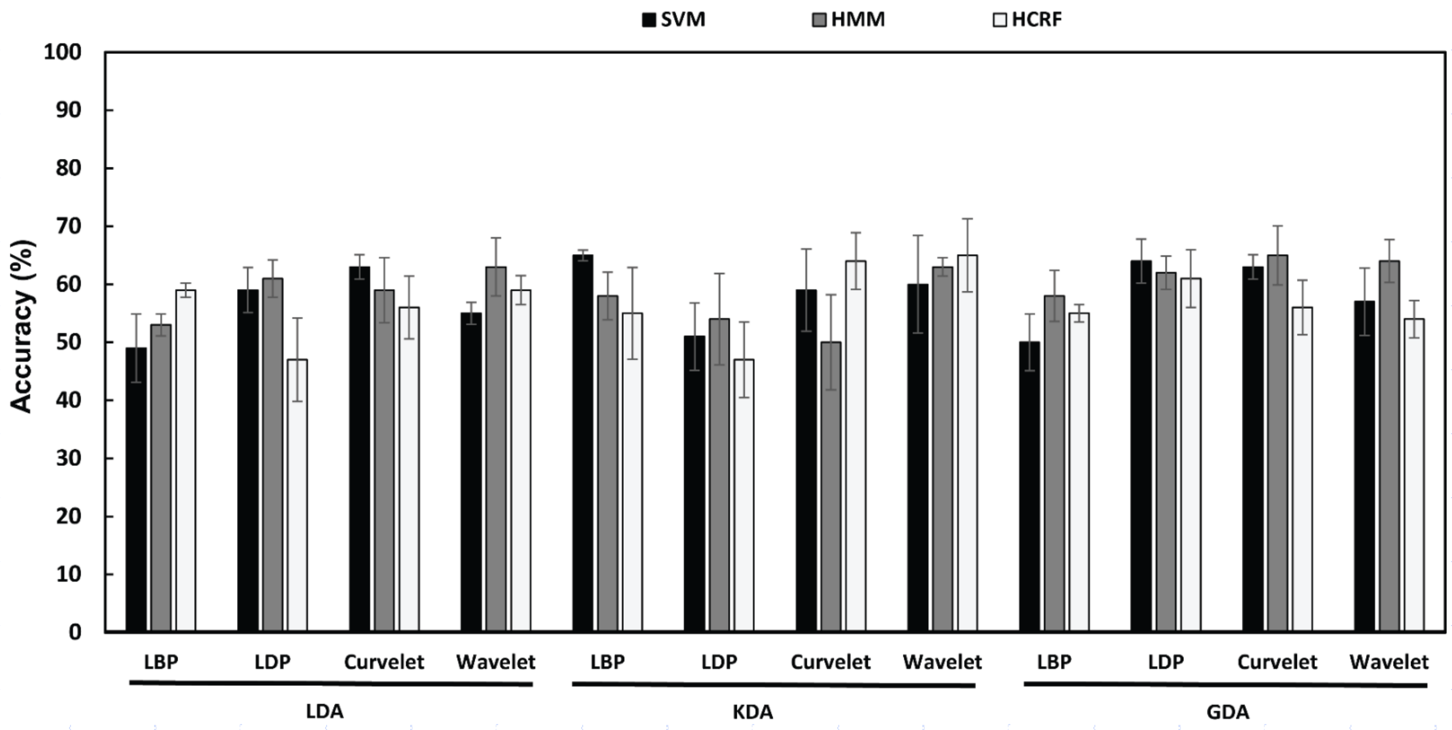


The average (bar and standard deviation whiskers) classification rates from the evaluation of the standard FER methods using emulated dataset

- ***Siddiqi, et. al***., "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Systems (SCI, IF: 0.619), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

- First Experiment: Results of the Standard Methodologies using Semi-naturalistic Dataset

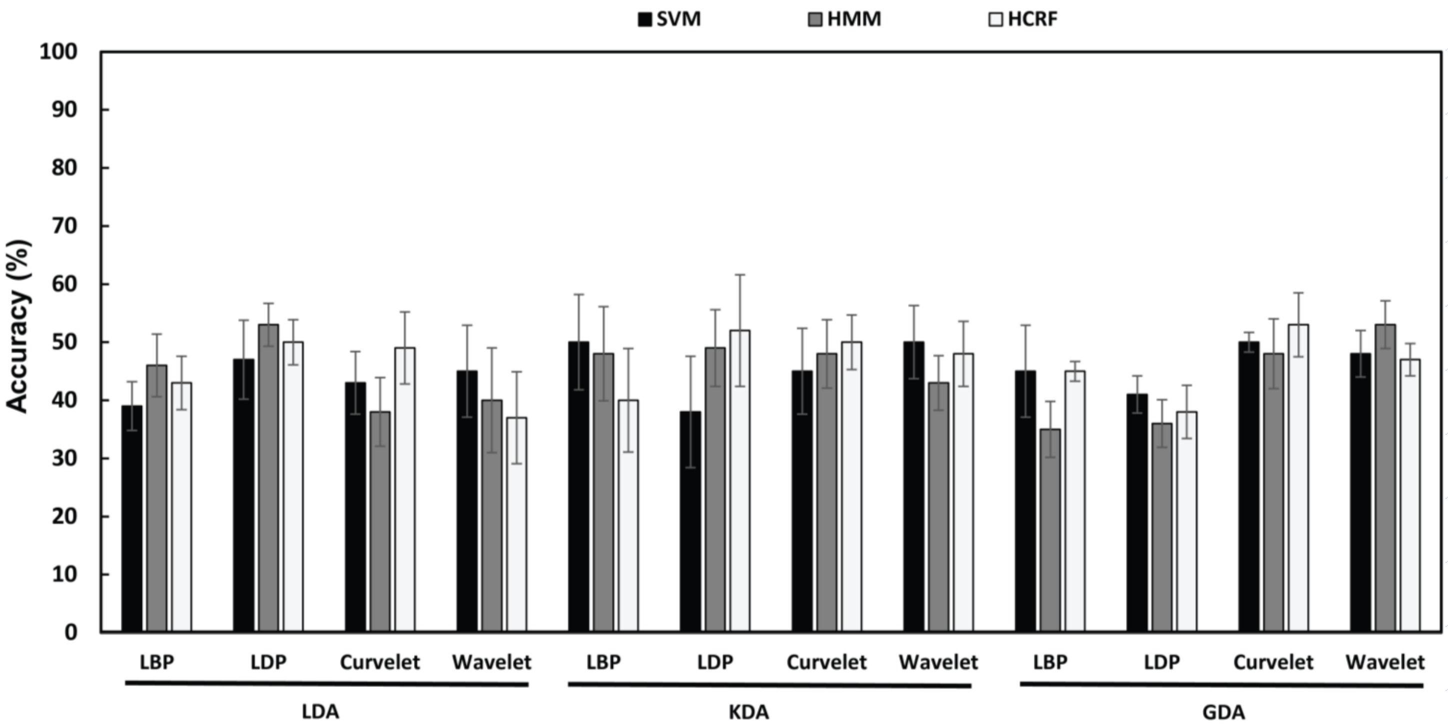


The average (bar and standard deviation whiskers) classification rates from the evaluation of the standard FER methods using semi-naturalistic dataset

- ***Siddiqi, et. al***., "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Systems (SCI, IF: 0.619), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

◆ First Experiment: Results of the Standard Methodologies using the Naturalistic Dataset

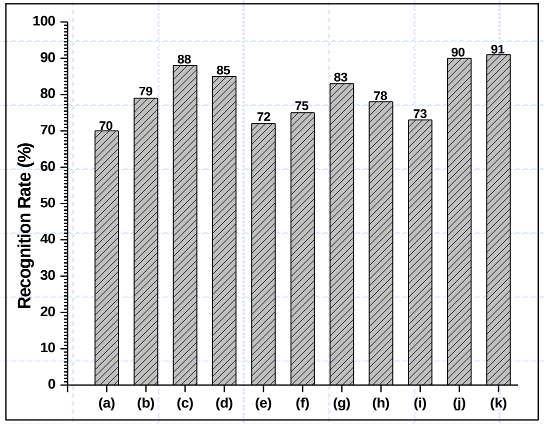


The average (bar and standard deviation whiskers) classification rates from the evaluation of the standard FER methods using naturalistic dataset

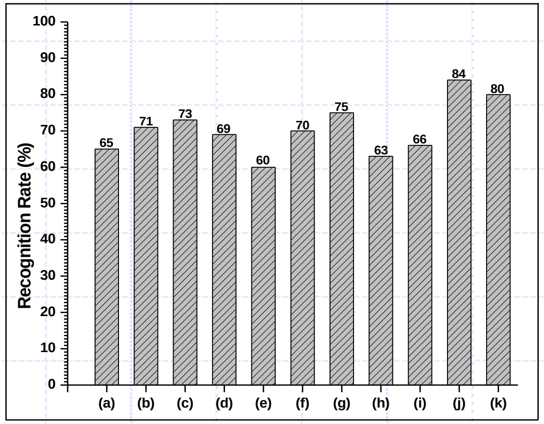
- ***Siddiqi, et. al***., "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Systems (SCI, IF: 0.619), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

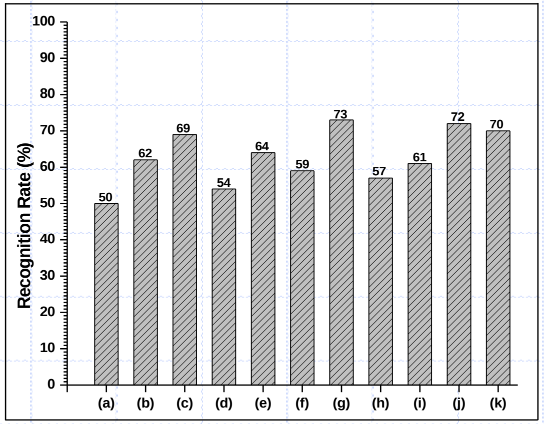
- Second Experiment: Results of the State-of-the-art using the Defined Datasets (Accuracy)



The average classification rates from the evaluation of state-of-the-art systems using the emulated dataset. The average recognition rate for all the systems is 80.4%



The average classification rates from the evaluation of state-of-the-art systems using the semi-naturalistic dataset. The average recognition rate for all the systems is 70.5%



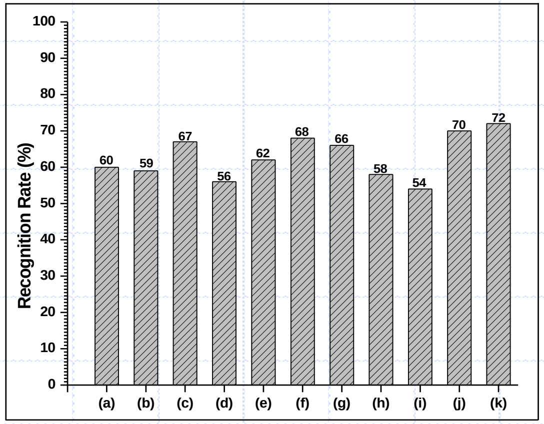
The average classification rates from the evaluation of state-of-the-art systems using the naturalistic dataset. The average recognition rate for all the systems is 62.6%

Where, (a) is [40], (b) is [41], (c) is [42], (d) is [43], (e) is [44], (f) is [45], (g) is [46], (h) is [47], (i) is [48], (j) is [49], and (k) is [50], respectively

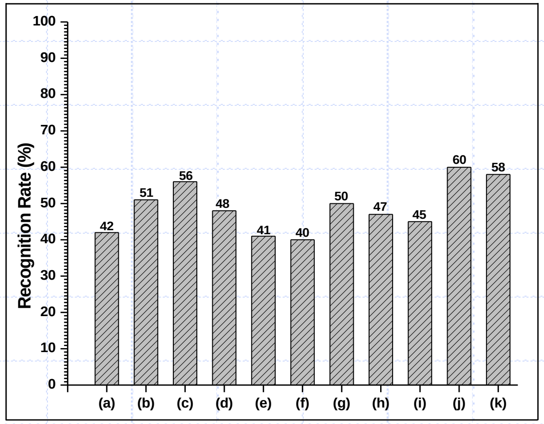
- ***Siddiqi, et. al***., "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Tools and Applications (SCIE, IF: 1.345), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

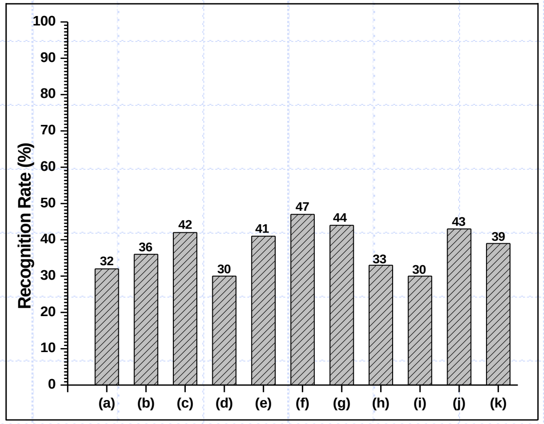
- Second Experiment: Results of the State-of-the-art using the Defined Datasets (Robustness)



Classification results of state-of-the-art systems. Training on emulated dataset and testing on semi-naturalistic and naturalistic datasets. The average recognition rate for all the systems are 63%.



Classification results of state-of-the-art systems. Training on semi-naturalistic dataset and testing on emulated and naturalistic datasets. The average recognition rate for all the systems are 48.9%.



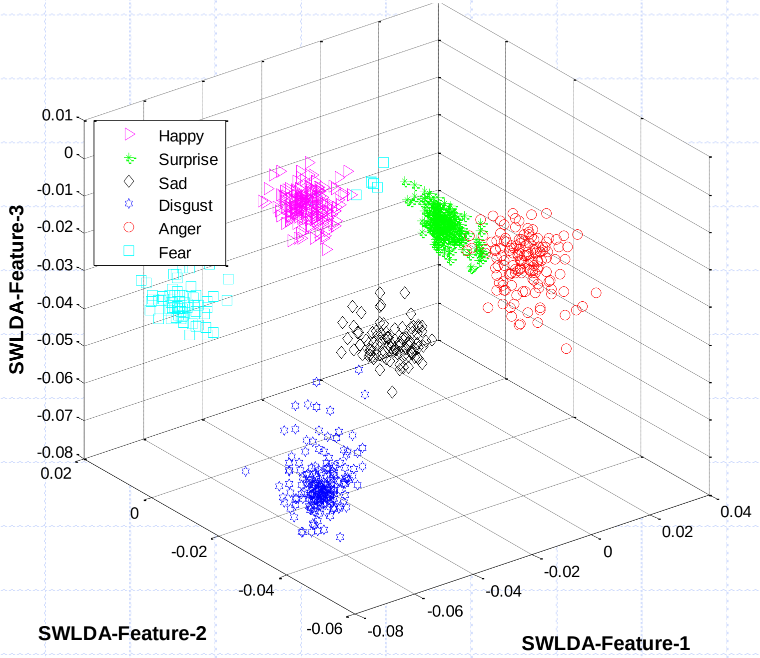
Classification results of state-of-the-art systems. Training on naturalistic dataset and testing on emulated and semi-naturalistic datasets. The average recognition rate for all the systems are 37.9%.

Where, (a) is [40], (b) is [41], (c) is [42], (d) is [43], (e) is [44], (f) is [45], (g) is [46], (h) is [47], (i) is [48], (j) is [49], and (k) is [50], respectively

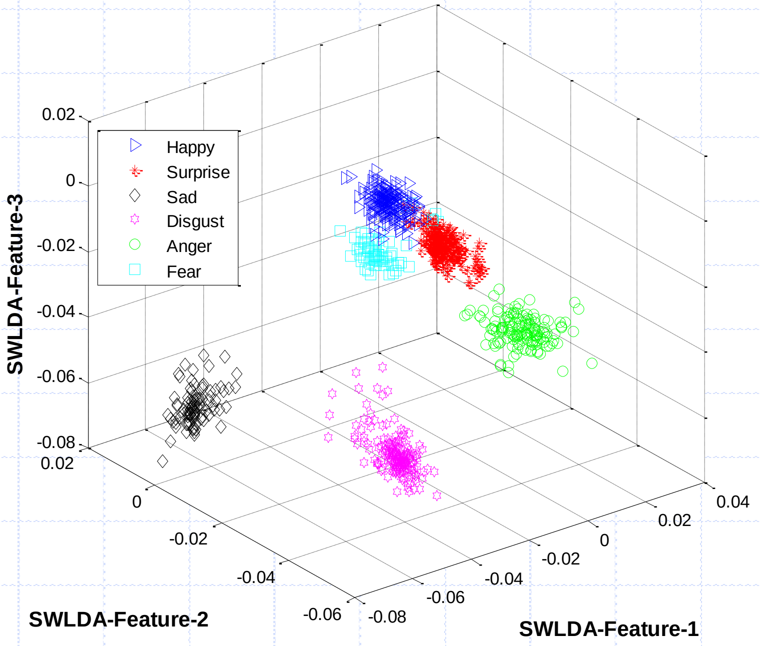
- ***Siddiqi, et. al.***, "Evaluating Facial Expression Recognition Methodologies in Real-World Situations by using YouTube-based Datasets ", Multimedia Tools and Applications (SCIE, IF: 1.345), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

- Third Experiment: Results of the Proposed Spontaneous FER System using IMFDB, and USTC-NVIE (Spontaneous-based) Datasets



3D-feature plot of the proposed system on USTC-NVIE dataset (93%)

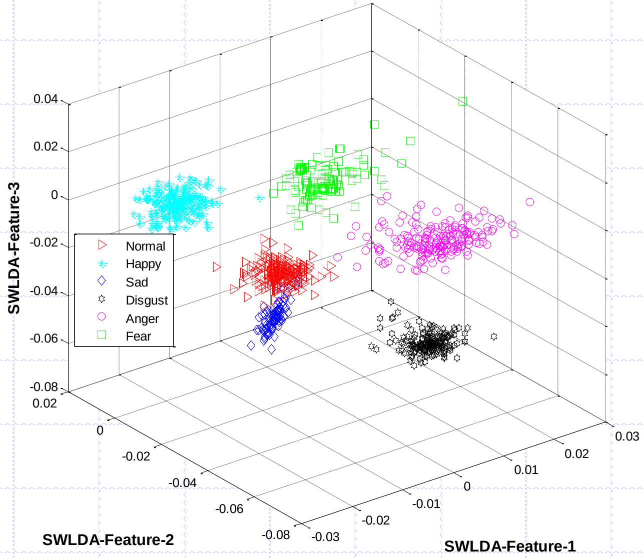


3D-feature plot of the proposed system on IMFDB dataset (90%)

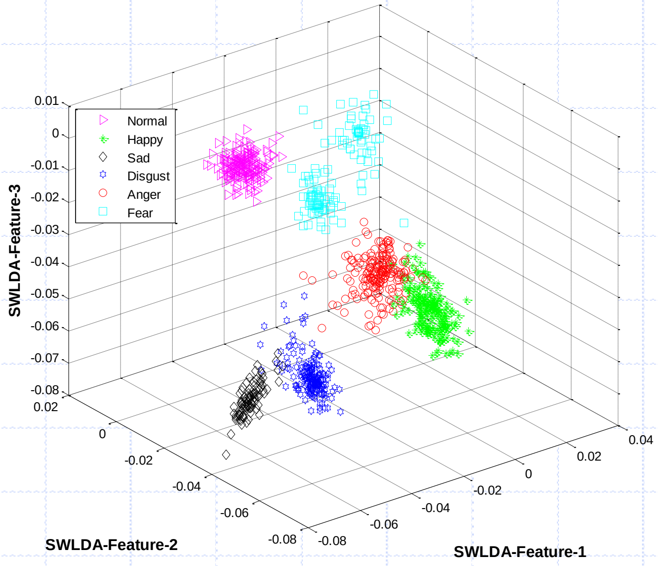
- ***Siddiqi, et. al***., "Spontaneous-based Facial Expression Recognition System using Real-time YouTube Dataset", IEEE Transactions on Pattern Analysis and Machine Intelligence (SCI, IF: 5.781), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

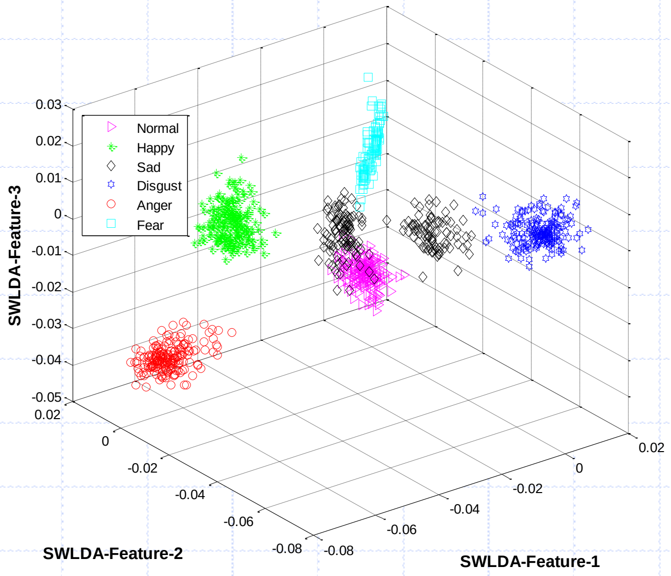
- Fourth Experiment: Results of the Proposed Spontaneous FER System using the Defined Datasets (Accuracy)



3D-feature plot of the proposed system on emulated dataset (94.16%)



3D-feature plot of the proposed system on semi-naturalistic dataset (88%)

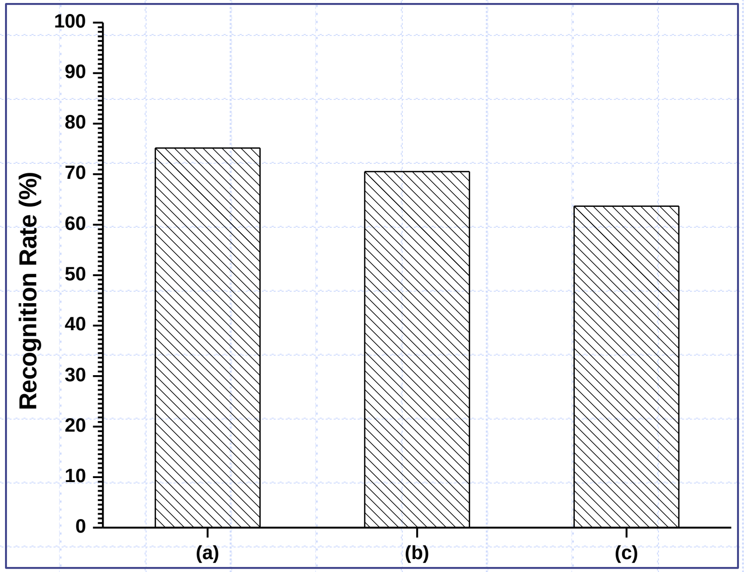


3D-feature plot of the proposed system on naturalistic dataset (85.83%)

- ***Siddiqi, et. al***., "Spontaneous-based Facial Expression Recognition System using Real-time YouTube Dataset", IEEE Transactions on Pattern Analysis and Machine Intelligence (SCI, IF: 5.781), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

- Fifth Experiment: Results of the Proposed Spontaneous FER System using the Defined Datasets (Robustness)

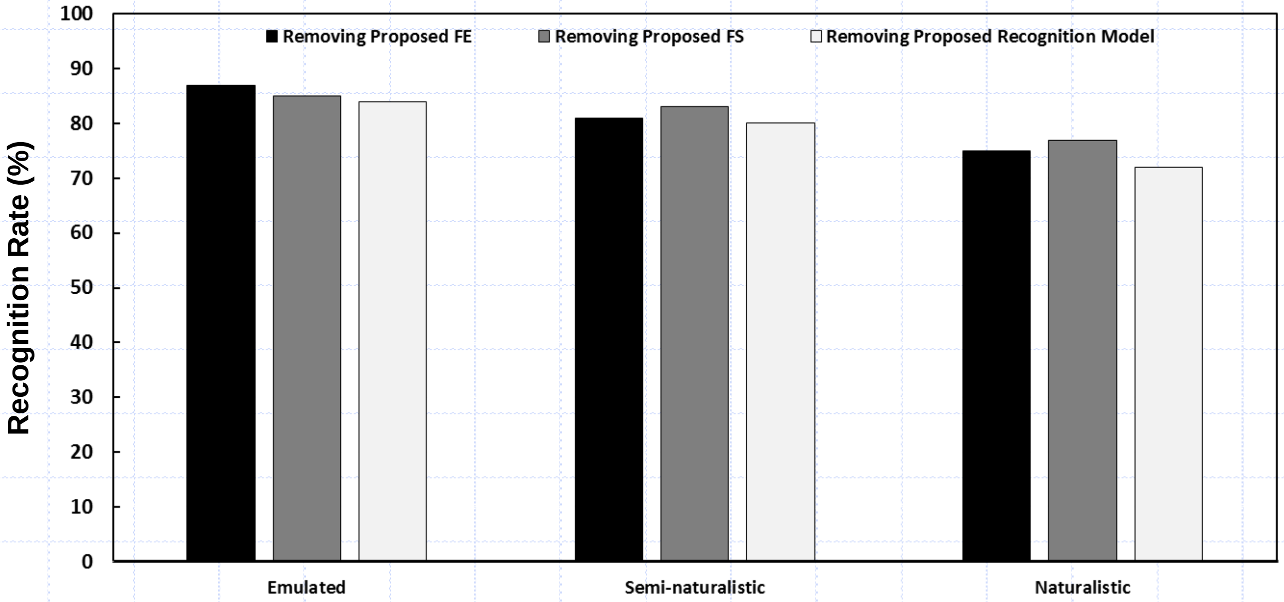


Recognition rate of the proposed system (a) training on emulated dataset and testing on semi-naturalistic and naturalistic datasets, (b) training on semi- naturalistic dataset and testing on emulated and naturalistic datasets, (c) training on naturalistic dataset and testing on emulated and semi- naturalistic datasets

- ***Siddiqi, et. al***., "Spontaneous-based Facial Expression Recognition System using Real-time YouTube Dataset", IEEE Transactions on Pattern Analysis and Machine Intelligence (SCI, IF: 5.781), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

- Sixth Experiment: Results of the Proposed Spontaneous FER System using the Defined Datasets (Under the Absence of Each Module)

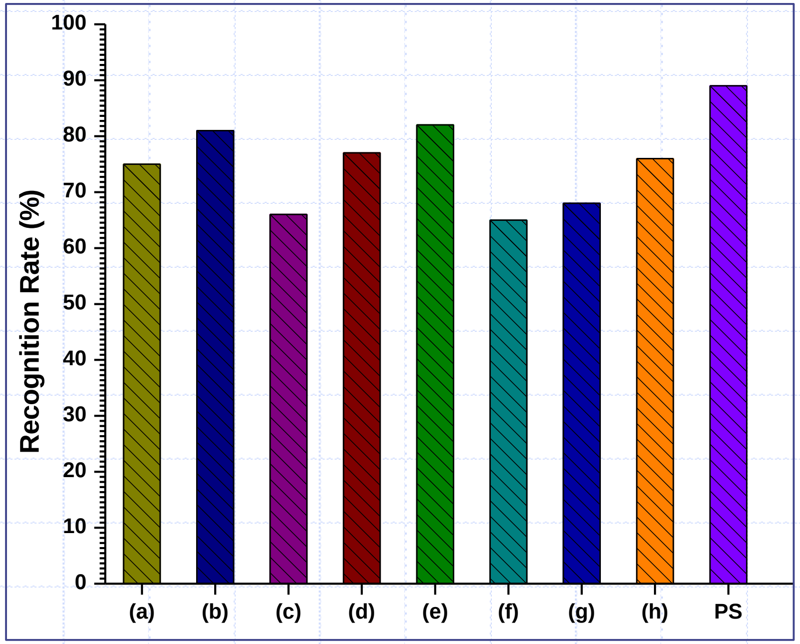


Recognition rates of the proposed system under the absence of individual proposed method (such as proposed feature extraction (FE), feature selection (FS), and recognition model) using all the three datasets in order to show the efficacy of each method

- ***Siddiqi, et. al***., "Spontaneous-based Facial Expression Recognition System using Real-time YouTube Dataset", IEEE Transactions on Pattern Analysis and Machine Intelligence (SCI, IF: 5.781), 2015 (under review)

Method 3: Experimental Results – Analyzing Defined Dataset

- Seventh Experiment: Comparison with some of the Existing Systems



Comparison results of the proposed system (PS) against some existing systems

Where, (a) is [51], (b) is [52], (c) is [34], (d) is [53], (e) is [54], (f) is [55], (g) is [56], and (h) is [21] respectively

- ***Siddiqi, et. al*.**, "Spontaneous-based Facial Expression Recognition System using Real-time YouTube Dataset", IEEE Transactions on Pattern Analysis and Machine Intelligence (SCI, IF: 5.781), 2015 (under review)

Uniqueness and Contributions

Hierarchical Recognition Scheme

- A hierarchical recognition scheme for solving within and between class variance problem

Robust FER System

- An unsupervised face detection that accurately detects and extracts the human faces
- A new feature extraction technique based on the pixel movement features
- Proposed the usage of a new and robust feature selection technique
  - Forward regression model
  - Backward regression model
- An improved version of the recognition model based on full covariance Gaussian distribution

Spontaneous-based FER

- Defined new, innovative, spontaneous, and naturalistic Dataset
  - Emulated Dataset
  - Semi-naturalistic Dataset
  - Naturalistic Dataset

Conclusion and Future Work

- This thesis contributes to:

High-within Class Variance and between-low class variance

- Designing and implementing of hierarchical recognition scheme using pose-based datasets for resolving high within-class and low between-class variance problems
- Achieved average 98% of accuracy using two publicly available standard datasets

Accuracy and robustness of FER

- Designing and implementing a robust FER based on different learning methods such as
  - active contour-based face detection,
  - facial movement-based feature extraction,
  - SWLDA-based feature selection, and
  - full covariance Gaussian distribution based recognition
- Compared to the existing systems, this work achieved average 97% of accuracy using four publicly available standard datasets

Robustness of FER in Spontaneous environment

- Defined and created new naturalistic datasets which considered the limitations of the existing datasets
- The system achieved average 89% of accuracy compared to the existing systems

- Future Research
  - In order to avoid the privacy concerns, depth camera will be utilized in the further study and then will check the accuracy and robustness of the proposed system

Best Achievement Award

Best Achievement Award

Student Number : 2012310058
Name : Muhammad Hameed Siddiqi

The person has achieved a remarkable results in year 2014. Thus "SW Research Institute for Global and Creative Human Resource Incubation" presents this award.

August. 28th. 2015

Derector, SW Research Institute for Global and Creative Human Resource Incubation(BK21 Plus)
& **Professor**, Department of Computer Science and Engineering, Kyunghee University

Choong Seon Hong

Publications

- SCI/ SCIE Journals (12)
  - First Author - 6 Published
  - Co-Author - 5 Published
  - Co-Author - 1 Minor Revision
- Non SCI Journals (1)
  - Co-Author - One Published
- Conferences (9)
  - First Author - 5 Publications
  - Co-Author - 4 Publications

- First Author - 2 Under Review
- Co-Author - 1 Under Review

Total Publications = 22

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THANK YOU!

Any questions or comments?