AHMEDABAD UNIVERSITY
School of Engineering and Applied Science

Human Gender and Age Estimation on Real-time Video

End Semester Presentation

Subject: CSP523- Machine Learning
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Introduction

- Human faces, convey a significant amount of nonverbal information to facilitate the real-world human-to-human communication
- Facial attributes, such as identity, age, gender, expression, and ethnic origin, play a crucial role in real facial image analysis
- **Applications:**
  - **Age specific human computer interaction** (**ASHCI**) system ensures young kids have no access to **internet pages** with adult materials
  - **Vending machine** can refuse to sell alcohol or cigarettes to the underage people
  - Ad-agency can find out what kind of scroll **advertisements** can attract the potential customers in what age ranges using a latent computer vision system

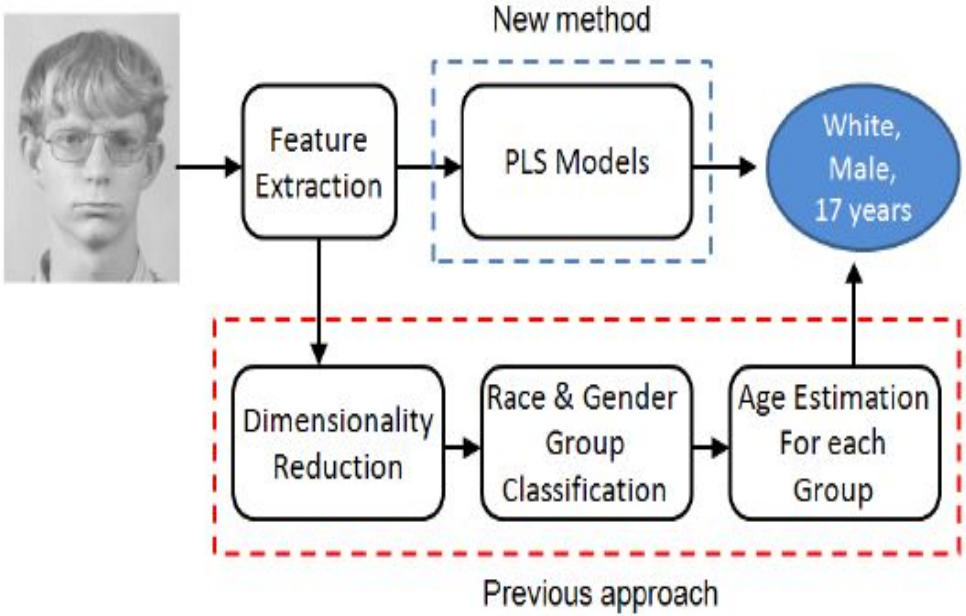
Problem Statement

Human Gender and Age Estimation on Real-time Video
via KPLS Regression

Literature Reviews

Age Estimation using Active Appearance Models and Support Vector Machine Regression [1]	**Image-Based Human Age Estimation by Manifold Learning and Locally Adjusted Robust Regression [2]**	**Simultaneous dimensionality reduction and human age estimation via kernel partial least squares regression [3]**	**A hierarchical approach for human age estimation [4]**
1. **Extract feature** using **AAM** (Active Appearance Models) 2. **Classify** images in different age groups using **SVM** (Support vector machine) 3. Use **SVR** (Support vector **regression**) for estimating age	1. **Normalize** images 2. Apply Age **manifold learning** for dimensionality reduction (**OLPP**) 3. Apply Robust **Regression** using Non-linear **SVR** (Gaussian kernel).	**1. Feature Extraction** 2. Use **Kernel-PLS** (Partial least square) to predict age	1. **Extract feature** using **AAM** (Active Appearance Models) 2. **Classify** images in different **age groups** by majority vote from result of different classifiers 3. Use **RVM** (Relevance vector machine) for estimating age

Implementation



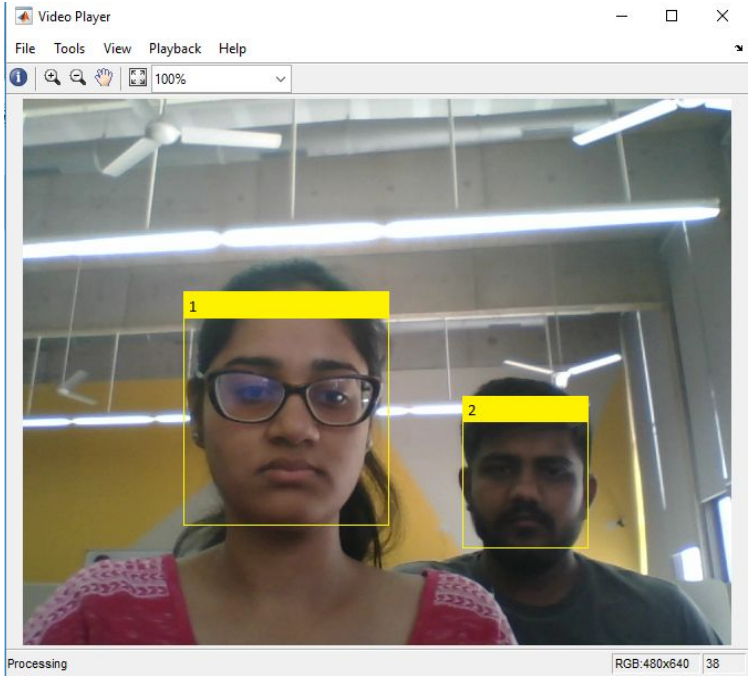
- Implemented **Biologically Inspired Features** for feature extraction from FG-NET dataset (1002 images)
- **Kernel Partial Least Square Regression** for age and gender estimation
- **Viola-Jones algorithm** for face detection for tracking on real-time video in MATLAB
- **K Nearest Neighbour for** age group classification (very young, young, middle, old age)

Results

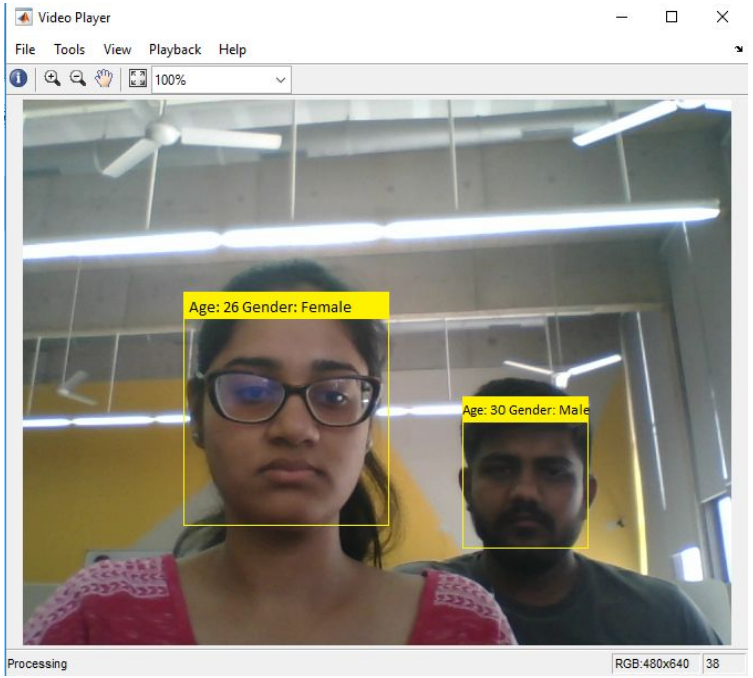
- Data set contains 1002 images from age 0 to **69**
- Considering images only of 21-30 age group, model gives best **MAE of 2.43** years and **Gender Accuracy 85.36%**
- **MAE: Average of absolute errors between true age and estimated age**
- Excluding images of 0-15 age group, model gives MAE of 7.79 years which is near to the ideal MAE for age estimation and Gender Accuracy 74.14%
- **Age Group Classification**:
  - Age groups are: very young (0-12), young(13-35), middle age(36-55), old age(56-above)
  - Classifier: k-Nearest Neighbors algorithm
  - Classification accuracy: **56%**

Results

Input



Output



Discussions

Case	Dimension	MAE (in Years)	Gender Accuracy (%)	Component
Age group:0-15 Training: 432 Testing: 150	100	2.71	51	25
Age group:11-20 Training: 255 Testing: 65	100	2.55	64.62	25
Age group: 21-30 Training: 100 Testing: 40	100	2.43	85.36	25
Age group: 31-above Training: 82 Testing: 15	100	7.59	80.00	25
Age group: ALL Training: 752 Testing: 250	100	8.64	54.80	20
Age group: Above 14 Training: 342 Testing: 116 R = 12, B = 8	100	7.79	74.14	20

Conclusion

- The PLS approach is evaluated based on **MAE Metric**. **Lower MAE implies better accuracy** of algorithm
- Approach perform dimensionality reduction and estimating age simultaneously, **no need to perform these steps separately**
- It can even deal with age, gender, and ethnicity altogether within a single learning step
- The very small FG-NET database (1002 images) is not good enough to fully explore the advantages on PLS
- KNN algorithm is a lazy learner and it is not robust to noisy data

Future Work

- **Training set needs to be enhanced** with different ethnicity and more number of images
- **Thresholding** in the system which restricts assigning age and gender to an unknown image (outlier detection)
- Accuracy can be increased by using **different kernel function**
- Different classifiers can be used for age categorization like SVM
- Age estimation with **GPU** (more computational power)
- Create threads by exploiting **multiple cores**

References

1. Luu, Khoa, et al. "Age estimation using active appearance models and support vector machine regression." Biometrics: Theory, Applications, and Systems, 2009. BTAS'09. IEEE 3rd International Conference on. IEEE, 2009.
2. G. Guo, Y. Fu, C. R. Dyer and T. S. Huang, "Image-Based Human Age Estimation by Manifold Learning and Locally Adjusted Robust Regression," in *IEEE Transactions on Image Processing*, vol. 17, no. 7, pp. 1178-1188, July 2008.
3. G. Guo and G. Mu, "Simultaneous dimensionality reduction and human age estimation via kernel partial least squares regression," *CVPR 2011*, Providence, RI, 2011, pp. 657-664.
4. Thukral, Pavleen, Kaushik Mitra, and Rama Chellappa. "A hierarchical approach for human age estimation." Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on. IEEE, 2012.

Thank you!