Human Gender and Age Estimation on Real-time Video

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Abstract**—** *Human age estimation has recently become an active research topic in computer vision and pattern recognition, because of many potential applications in reality. We are using the kernel partial least squares (KPLS) regression for age estimation. The KPLS (or linear PLS) method has several advantages over previous approaches: (1) the KPLS can reduce feature dimensionality and learn the aging function simultaneously in a single learning framework, instead of performing each task separately using different techniques; (2) the KPLS can find a small number of latent variables, e.g., 20, to project thousands of features into a very low-dimensional subspace, which may have great impact on real-time applications; and (3) the KPLS regression has an output vector that can contain multiple labels, so that several related problems, e.g., age estimation, gender classification, and ethnicity estimation can be solved altogether.*

Keywords— Biologically inspired features (BIF), feature extraction, KPLS, simultaneous feature dimensionality reduction

I. Introduction

Human faces, as important visual cues, convey a significant amount of nonverbal information to facilitate the real-world human-to-human communication. As a result, the modern intelligent systems are expected to have the capability to accurately recognize and interpret human faces in real time. Facial attributes, such as identity, age, gender, expression, and ethnic origin, play a crucial role in real facial image analysis applications including multimedia communication, human computer interaction (HCI), and security. In such applications, various attributes can be estimated from a captured face image to infer the further system reactions. For example, if the user's age is estimated by a computer, an age specific human computer interaction (ASHCI) system may be developed for secure network/ system access control.

The ASHCI system ensures young kids have no access to internet pages with adult materials. A vending machine, secured by the ASHCI system, can refuse to sell alcohol or cigarettes to the underage people. In image and video retrieval, users could retrieve their photographs or videos by specifying a required age range. Ad-agency can find out what kind of scroll advertisements can attract the passengers (potential customers) in what age ranges using a latent computer vision system.

In this paper, we propose a novel scheme for aging extraction and automatic age estimation using kernel partial squares regression.

II. Literature Review

We read about current approaches to the age estimation problem. Based on the MAE(Mean absolute error) as stated in the papers, we chose KPLS(Kernel Partial least square) which had minimum error on FG-Net dataset. Different approaches which we read from paper exploration are:

A. Age Estimation using Active Appearance Models and Support Vector Machine Regression [1]

- Extract feature using AAM(Active Appearance Models)

- Classify images in different age groups using SVM(Support vector machine).
- Use SVR(Support vector regression) for estimating age.

B. Image-Based Human Age Estimation by Manifold Learning and Locally Adjusted Robust Regression[2]

- Normalize images.
- Apply Age manifold learning for dimensionality reduction (OLPP).
- Apply Robust Regression using Non-linear SVR (Gaussian kernel).

C. Simultaneous dimensionality reduction and human age estimation via kernel partial least squares regression [3]

- Feature Extraction.
- Use Kernel-PLS(Partial least square) to predict age.

D. A hierarchical approach for human age estimation [4]

- Extract feature using AAM(Active Appearance Models)
- Classify images in different age groups by majority vote from result of different classifiers.
- Use RVM(Relevance vector machine) for estimating age.

Approach A and D estimate age by doing first classification. So accuracy depends on correctness of classification. Below table describes MAE of all approaches described in literature review on FG-NET database.

Approach	**MAE**
A. (SVM + SVR)	4.37
B. (OLPP + LARR)	5.07
C. (KPLS)	4.18
D. (Ensemble + RVM)	6.2

III. Our approach

Implemented Biologically Inspired Features (BIF) for feature extraction, Kernel Partial Least Square (KPLS) Regression for age and gender estimation, Viola-Jones algorithm for face detection for tracking on real-time video in MATLAB.

in the two step process, the first step includes extracting features from images. Thereafter, our PLS model will use a single step for estimating age instead of doing three separate operations namely Dimensionality reduction, Race & Gender group classification and age estimation. The PLS is a wide class of methods for modelling relations between set of observed variables by means of latent variables.

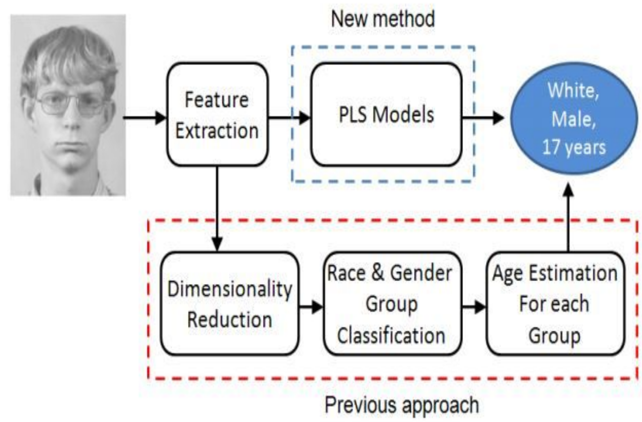


Figure 1: PLS model [3]

1. Linear PLS Regression:

Consider the general setting of a linear PLS algorithm to model the relation between two data sets denoted by $X \subset R^N$ and $Y \subset R^M$. PLS models the relations between these two blocks by means of score vectors. After observing n data samples, PLS decomposes the $(n \times N)$ matrix of zero-mean variables X and the $(n{\times}M)$ matrix of zero-mean variables Y into the form

$$\mathbf{X = TP^T + E}$$
$$\mathbf{Y = UQ^T + F}$$

T and U are $(n \times p)$ matrices of the p extracted score vectors (components, latent vectors), the $(N \times p)$ matrix P and the $(M \times p)$ matrix Q represent matrices of loadings, and the $(n \times N)$ matrix E and the $(n \times M)$ matrix F are the matrices of residuals.
The PLS method is based on the nonlinear iterative partial least squares (NIPALS) algorithm.
Find weight vectors **w**, **c** such that

$[\text{cov}(\mathbf{t}, \mathbf{u})]^2 = [\text{cov}(\mathbf{Xw}, \mathbf{Yc})]^2$

$$= \max_{|r|=|s|=1}[\text{cov}(\mathbf{Xr}, \mathbf{Ys})]^2$$

A linear inner relation between the score vectors t and u exists.

$$\mathbf{U = TD + H}$$

D is a (p × p) diagonal matrix and H is the matrix of residuals.
We can derive:

$$\mathbf{Y = TDQ^T + (HQ^T + F)}$$

and this defines the linear PLS regression model

$$\mathbf{Y = TC^T + F^*}$$

where $C^T = DQ^T$ denotes the (p × M) matrix of regression coefficients and $F* = HQ^T + F$ is the residual matrix

2. Kernel PLS Regression:

Linear PLS models may not perform well when strong nonlinear relation exists between X and Y. The Linear PLS model can be expressed as:

$$\mathbf{Y = XB + F^*}$$

where $\mathbf{B = X^TU(T^TXX^TU)^{-1}T^TY}$

Define the Gram matrix K of the cross dot products between all mapped input data points, i.e., $K = \Phi\Phi^T$, where Φ denotes the matrix of the mapped X-space data {Φ(xi) ∈ F}n i=1, where F is the high-dimensional feature space. The kernel trick implies that the elements i, j of K are equal to the values of the kernel function k(xi, xj). R is Rotation and B is Band. The default Rotation and Band are 8 and 4 respectively.

$$\mathbf{Y = \Phi B + F^*}$$

where the estimate of B is

$$\mathbf{B = \Phi^TU(T^TKU)^{-1}T^TY}$$

Let $\mathbf{d^m = U(T^TKU)^{-1}T^Ty^m}$, m = 1,...,M

Then the kernel PLS regression estimate of the m-th output for a given input sample x will be

$$\mathbf{y\hat{}^m = \Phi(x)^T\Phi^Td^m = \sum_{i=1}^{n} d_i^m k(x, xi)}$$

IV. Important Results and Discussions

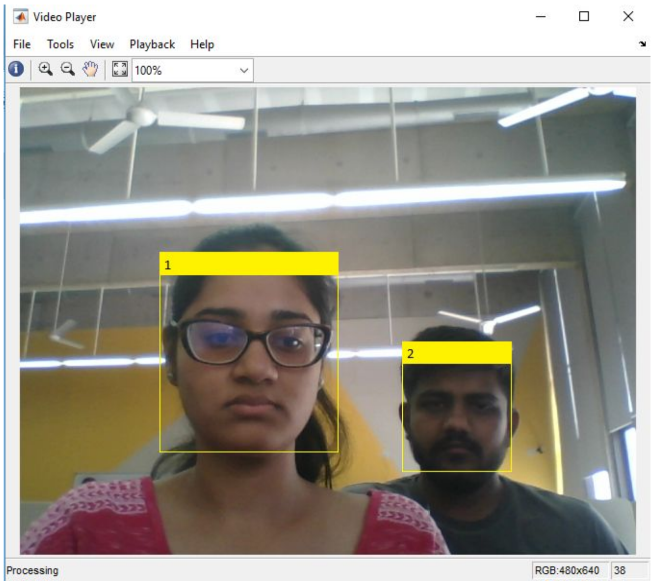
Case	Dimension	MAE (in Years)	Gender Accuracy (%)	Component
Age group:0-15 Training: 432 Testing: 150	100	2.71	51	25
Age group:11-20 Training: 255 Testing: 65	100	2.55	64.62	25
Age group: 21-30 Training: 100 Testing: 40	100	2.43	85.36	25
Age group: 31-above Training: 82 Testing: 15	100	7.59	80.00	25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

- When excluding 0 - 15 age group person images, model gives MAE of 7.79 years which is near to the ideal MAE for age estimation.
- When we train model separately for each age group, MAE improves by good margin.

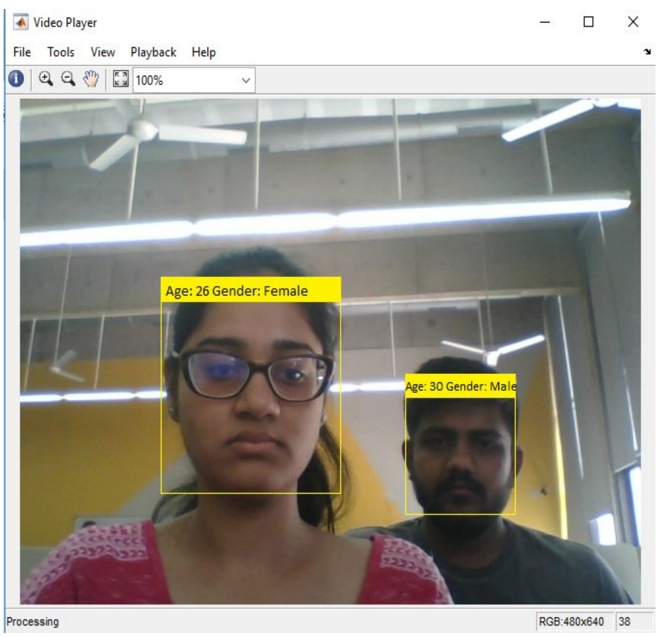
- When considering only images of 21-30 age group, model gives best MAE for that group.
- **Age Group Classification**: Given an image, classify that image in appropriate age group

- Age groups are: very young, young, middle age, old age
- Classifier: k-Nearest Neighbors algorithm
- Classification accuracy: 56%

- KNN Classifier is a very simple classifier, works well on basic recognition problems. The main disadvantage is that it is a lazy learner also it is not robust to noisy data.



Input image



Output image

V. Conclusions

We have investigated the elegant method called Partial least squares model. The approach is evaluated based on MAE (Mean Absolute Error) metric. Lower MAE implies better accuracy of algorithm. The PLS model is useful not only for dimensionality reduction, but also to learn the aging function as well. It can even deal with age, gender, and ethnicity altogether within a single learning step. The MAE presented is evaluated on FG-NET database. The very small FG-NET database is not good to fully explore the advantages on PLS. Thus for improving age estimation, the training database should be large enough.

VI. Acknowledgement

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VII. 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.