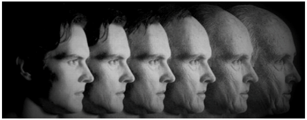
Hierarchical Age Estimation from Unconstrained Facial Images

STIC-AmSud



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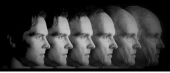
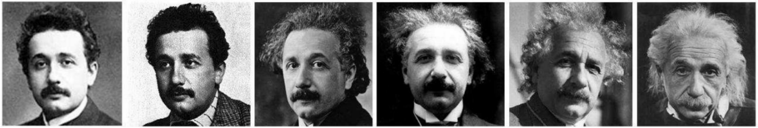
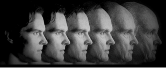
Curitiba, Oct 2014

Outline



The appearance of a human face changes significantly by aging.



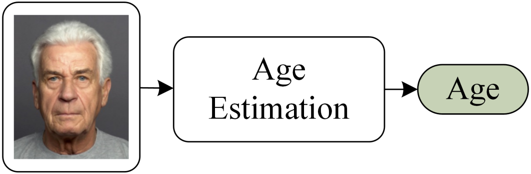


- **Craniofacial growth** (from birth to adulthood)
  - Face contour
  - Facial component shape (e.g., eyes, nose and mouth)
- **Skin aging** (from adulthood to old age)
  - Reduction of muscle strength / elasticity
  - Wrinkles
  - Skin color (Darker)
  - Spots

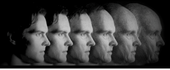
Characteristics of the aging process

- Slow
- Irreversible
- Personalized
  - Intrinsic factors
    - Genetics
    - Gender
    - Ethnicity
  - Extrinsic factors
    - Health
    - Lifestyle
    - Environment

Implementing algorithms that enable the estimation of a person's age based on features derived from his/her face image.



- Security control
- Surveillance
- Human-computer interaction
- Facial recognition robust to age progression



1 Introduction

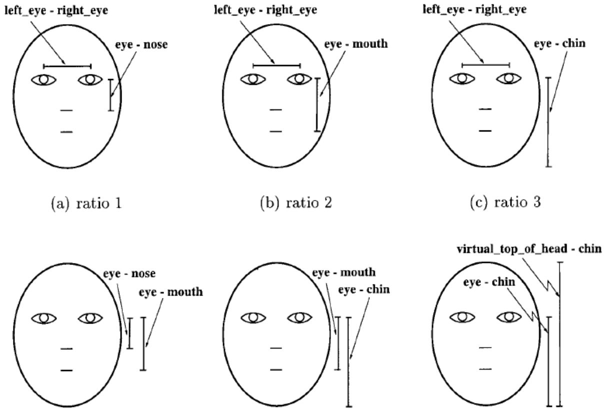
2 State of the art overview
- Age image representation
- Age estimation method

3 Proposed method

4 Experimental results

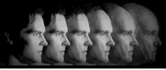
5 Summary

- **Anthropometric models** - Kwon and Lobo [1]
  - Based on the geometric ratios of facial components.

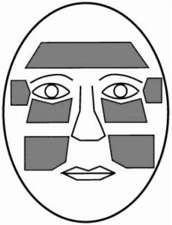


(a) ratio 1 (b) ratio 2 (c) ratio 3

(d) ratio 4 (e) ratio 5 (f) ratio 6

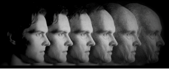


- Might be useful for young ages, but is not appropriate for adults.
- Kwon and Lobo further analyse the wrinkles to separate young adults from senior adults.

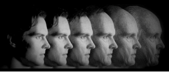


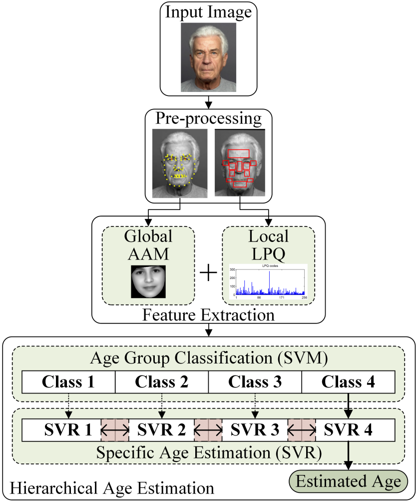
- **Active appearance models** - Luu et al. [2]
  - Based on the statistical face model AAM proposed by Cootes et al. [3].
- **AGES - AGing pattErn Subspace** - Geng et al. [4]
  - Regard the sequence of an individual's aging face images as a whole rather than separately (aging pattern).
- **Appearance models** - Choi et al. [5]
  - Based on aging related features extracted from face images.
    - **Global features** - AAM [2]
    - **Local features** - Gabor wavelet and LBP [5]

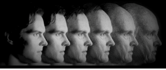
Age estimation method



- **Multi-class classification**
  - k-Nearest Neighbors (KNN) [6]
  - Artificial Neural Networks (ANN) [7]
  - Support Vector Machine (SVM) [8]
- **Regression**
  - Logistic Regression [9]
  - Support Vector Regression (SVR) [9]
- **Hybrid approach**
  - SVM + SVR [8]



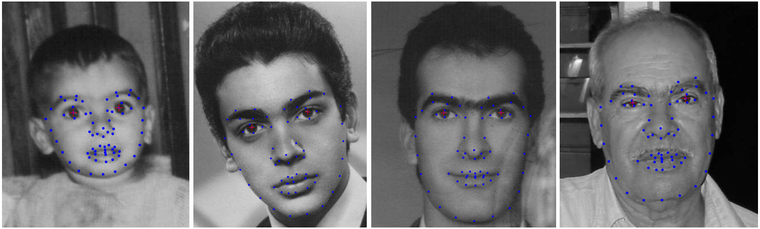

Input Image
Pre-processing
Global
AAM
Local
LPQ
LPQ codes
Feature Extraction
Age Group Classification (SVM)
Class 1
Class 2
Class 3
Class 4
SVR 1
SVR 2
SVR 3
SVR 4
Specific Age Estimation (SVR)
Hierarchical Age Estimation
Estimated Age



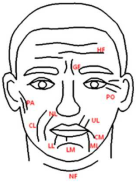
- FG-NET Aging
  - Publicly available.
  - 1,002 facial images for 82 subjects.
  - 0 to 69 years.
  - 50% between 0 to 13 years.
  - Provides 68 landmarks.

Pre-processing

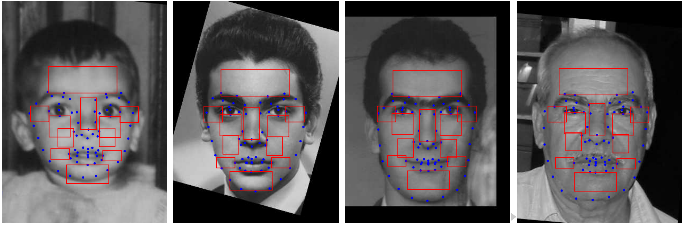
- To reduce the influence of inconsistent colors
  - Grayscale conversion
- To improve the accuracy of facial components localization
  - Non-reflective similarity transformation based on two eyes
  - Same inter-pupillary distance



- Based on the various types of facial wrinkles described by Lemperle [5].



HF - Horizontal forehead lines
GF - Glabellar frown lines
UL - Upper radial lip lines
LL - Lower radial lip lines
ML - Marionete lines
CM - Corner of the mouth lines
PO - Periorbital lines
PA - Preauricular lines
CL - Cheek lines
NL - Nasolabial folds
LM - Labiomental crease
NF - Horizontal neck folds



- The 11 skin areas of a 69 years old subject

1. Left corner of the mouth lines (36x21)

2. Right corner of the mouth lines (36x21)

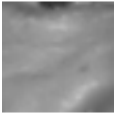
3. Left periorbital lines (36x31)

4. Right periorbital lines (36x31)

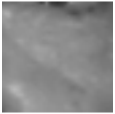
5. Left nasolabial folds (31x36)

6. Right nasolabial folds (31x36)

7. Left cheek lines (41x41)



8. Right cheek lines (41x41)



9. Chin crease (81x36)

10. Top nose (31x61)

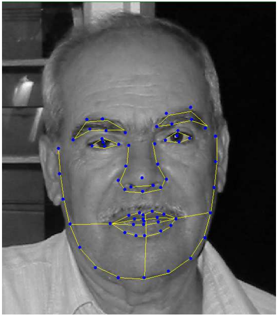
11. Horizontal forehead lines (131x51)

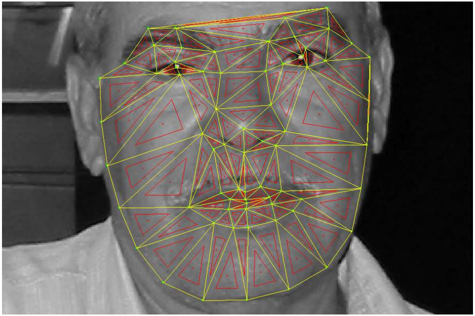
Age image representation

- **Global features**
  - Active Appearance Model (AAM)
- **Local features**
  - Local Binary Patterns (LBP)
  - Local Phase Quantization (LPQ)
  - Gabor wavelets
- **Feature level fusion**
  - Global + Local features

Active appearance models (AAM)

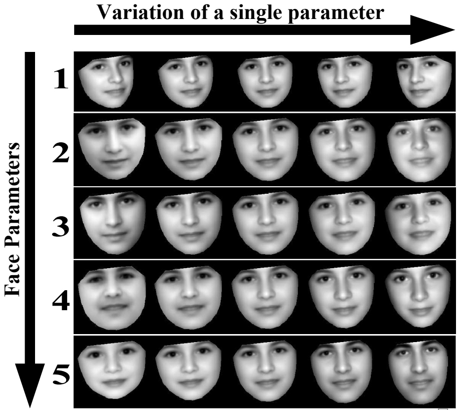
- 68 landmarks and triangles used for texture description





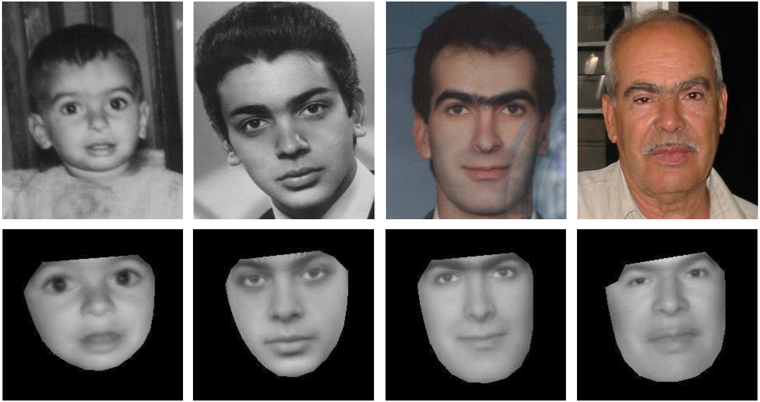
Active appearance models (AAM)

- Variation of the first five combined features in both directions of their learned standard deviation



Active appearance models (AAM)

- Some fitting results



Local Binary Patterns (LBP)

- Each pixel is compared against its neighbors

118	190	6
69	106	110
42	31	106

(a) 3×3 image region

1	1	0
0		1
0	0	0

(b) Threshold results (code 10100001_2)

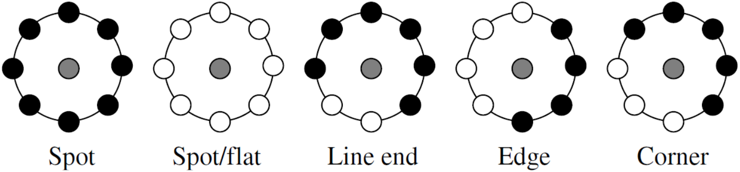
1	128	64
2		32
4	8	16

(c) Pixel weights

1	128	0
0	**161**	32
0	0	0

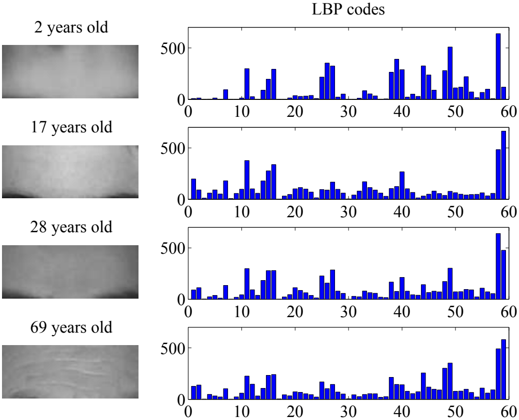
(d) Code and contributions

- Different patterns detected by the LBP operator



Local Binary Patterns (LBP)

- Histograms of the $\text{LBP}_{8,2}^{u2}$ codes for the forehead skin area.

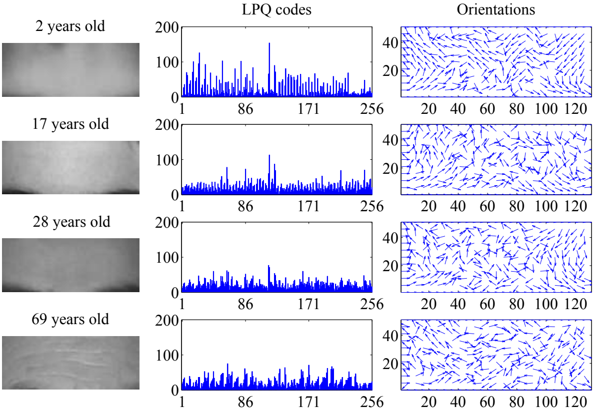


Local Phase Quantization (LPQ)

- Powerful feature extractor that has been used as an alternative to the widely used LBP [10].
- Very robust to blur, lighting and facial expression variations present in real world images.
- Phase is computed locally for a window in every skin area position and presents the resulting codes as a histogram.

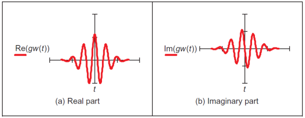
Local Phase Quantization (LPQ)

- Histograms of the $LPQ_{5\times5}$ codes for the forehead skin area and unit vectors illustrating the characteristic orientations.

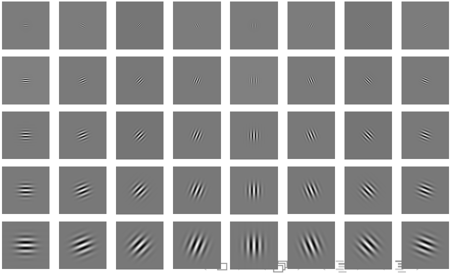


Gabor wavelet

- Successfully applied to facial expression recognition
- Sinewave modulated by a Gaussian envelope
- The function of the wavelet transform is to determine where and how each wavelet occurs in the image
- Example of Gabor wavelet and filtes for 8 orientations and 5 scales.

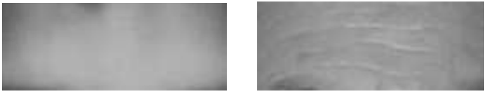


(a) Real part (b) Imaginary part

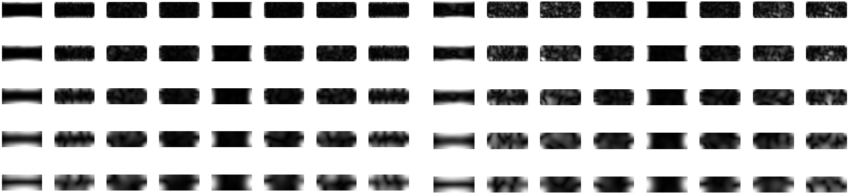


Gabor wavelets

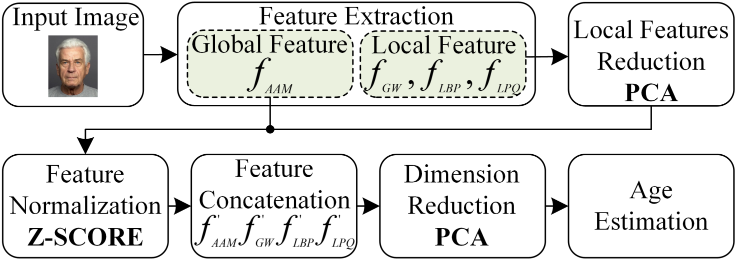
- Forehead skin area of 2 and 69 year old subjects.

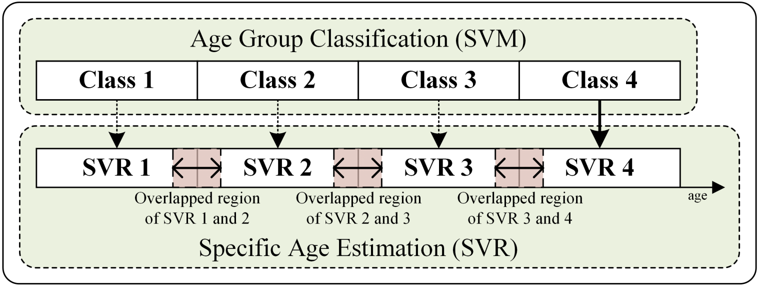


- Magnitudes after Gabor wavelet transform in the forehead skin areas (2 and 69 years, respectively).

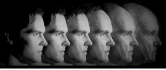


Feature level fusion





Age Group Classification (SVM)
Class 1
Class 2
Class 3
Class 4
SVR 1
SVR 2
SVR 3
SVR 4
age
Overlapped region of SVR 1 and 2
Overlapped region of SVR 2 and 3
Overlapped region of SVR 3 and 4
Specific Age Estimation (SVR)



- **Mean Absolute Error** (MAE)
  - An indicator of the average performance of the age estimation.

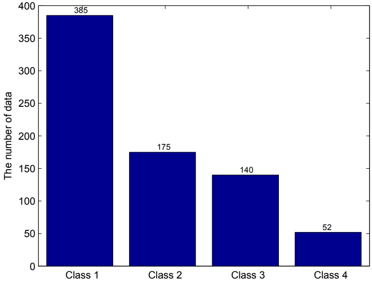
$$MAE = \frac{\sum_{i=1}^{N} |\hat{a} - a|}{N}$$

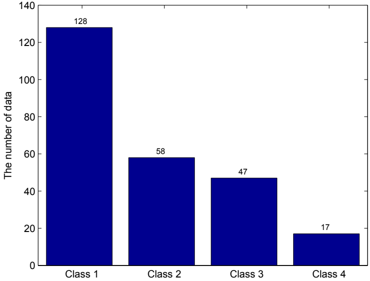
- **Cumulative Score** (CS) at different absolute error levels l.
  - An indicator of accuracy of the age estimation.

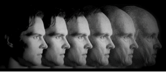
$$CS(l) = \frac{N_{e \leq l}}{N} \times 100\%$$

Train and test data distribution for each class

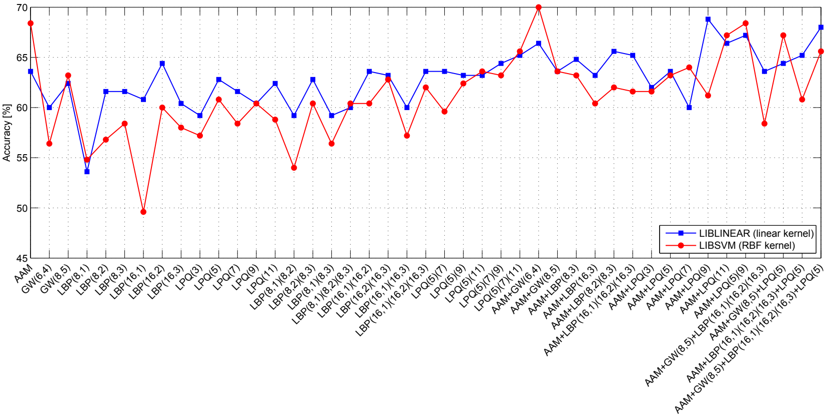
Class	Age range	Train	Test
1	0-13	385	128
2	14-21	175	58
3	22-39	140	47
4	40-69	52	17
Total	0-69	752	250





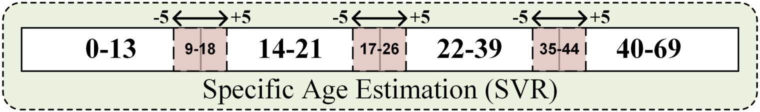


- Classification accuracy for different features set.

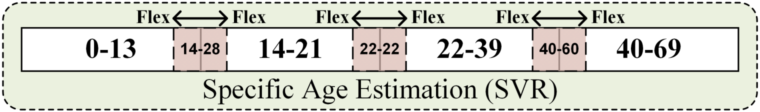


Specific age estimation

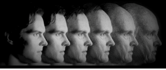
- Fixed overlapped age ranges



- Flexible overlapped age ranges

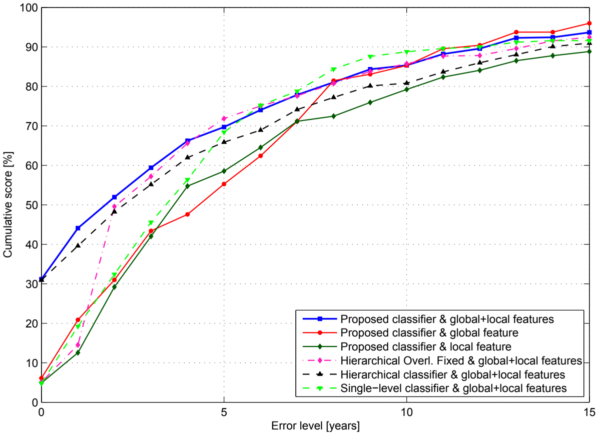


Specific age estimation



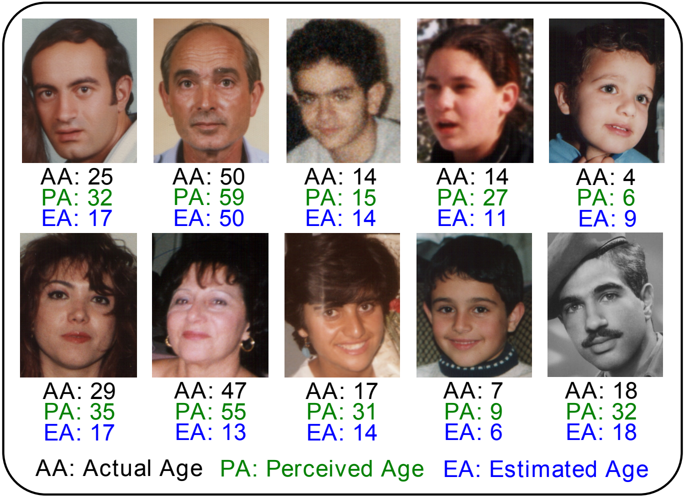
Feature set	Hierarchical *MAE*	Hierarchical Overlapped Fixed *MAE*	Hierarchical Overlapped Flex *MAE*
AAM	5.91	5.11	5.65
$GW_{8,5}$	7.54	7.40	7.44
$LBP_{8,2}$	9.51	9.68	9.22
$LPQ_{5\times5}$	6.60	6.49	6.26
$LPQ_{7\times7}$	7.31	7.35	6.79
$LBP_{(16,1)(16,2)(16,3)}$	6.16	6.28	6.03
$AAM+GW_{6,4}$	6.02	5.98	6.06
$AAM+LBP_{(16,1)(16,2)(16,3)}$	5.42	6.53	5.17
$AAM+LPQ_{5\times5}$	**5.13**	5.19	4.73
$AAM+LPQ_{7\times7}$	**5.31**	**5.30**	**4.50**
$AAM+GW_{8,5}+LBP_{(16,1)(16,2)(16,3)}$	5.28	6.06	4.86
$AAM+GW_{8,5}+LPQ_{5\times5}$	5.36	**4.85**	5.12
$AAM+LBP_{(16,1)(16,2)(16,3)}+LPQ_{5\times5}$	6.38	5.33	4.96
$AAM+GW_{8,5}+LBP_{(16,1)(16,2)(16,3)}+LPQ_{5\times5}$	5.17	5.79	5.32

- The CS for the proposed approach at error levels from 0 to 15 years.

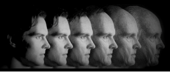


Human estimation

- Research with 20 people.
- 250 images from the FG-NET test set.
- 10 facial images each.
- To estimate the perceived age.

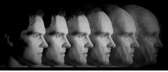

AA: 25
PA: 32
EA: 17
AA: 50
PA: 59
EA: 50
AA: 14
PA: 15
EA: 14
AA: 14
PA: 27
EA: 11
AA: 4
PA: 6
EA: 9
AA: 29
PA: 35
EA: 17
AA: 47
PA: 55
EA: 13
AA: 17
PA: 31
EA: 14
AA: 7
PA: 9
EA: 6
AA: 18
PA: 32
EA: 18
AA: Actual Age
PA: Perceived Age
EA: Estimated Age

Comparison to other works



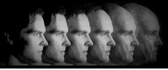
Methods of age estimation	MAE
WAS [11]	8.06
AGES [4]	6.77
BM [12]	5.33
RPK [13]	4.95
Luu [2]	4.37
Duong et al. [14]	4.74
Choi et al. [5]	4.65
Kohli et al. [15]	3.85
Human estimation	6.52
Proposed AAM+LPQ$_{7\times7}$	**4.50**

Outline



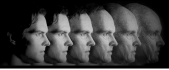
- A novel age estimation method combining global features extracted by AAM and local features extracted by LPQ has been proposed.
- A new hierarchical age estimation method with overlapped flexible age classes in the regression step is proposed.
- LPQ shows that it is very robust not only to blur but also to other challenges such as lighting and expression variations present in the FG-NET.
- Despite its simpleness and robustness, LPQ was shown to be highly discriminative producing very good results for age estimation.

Summary



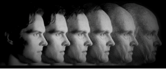
- Age estimation is still a challenging problem.
- Several factors could influence the aging process.
- How to find a robust representation featuring remains an open problem, and this work contributes to increase the robustness to such perturbations through local phase features.

Thank You!



Questions?

References I



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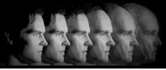

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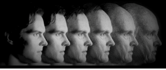

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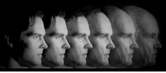

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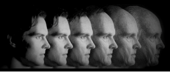

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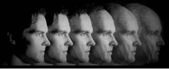

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