Face Verification Across Age Progression
Using Gradient Orientation Pyramids and SVM

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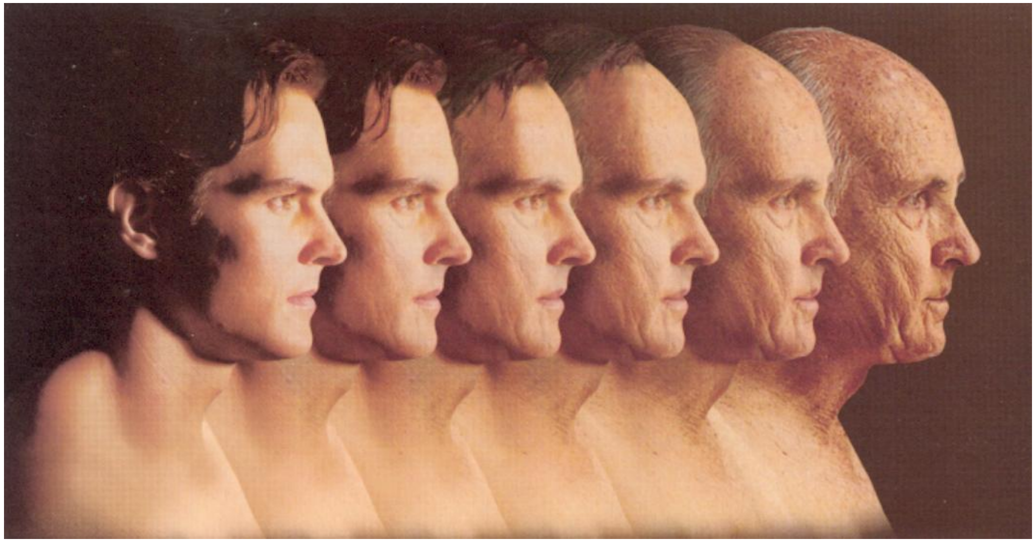


Problem statement & Motivation

- Face **verification** is a two-class classification problem, as opposed to the face **recognition** process
  - Given an input image pair I1 and I2, assign it as either **intrapersonal** (the same person) or **extrapersonal** (different individuals)
- **Problem**: identify / verify a person based on an image from their past
- Area of application:
  - Surveillance
  - Passport verification (or other documents)
  - Human-computer interaction
  - Identifying missing persons over time
- Face verification across age progression has been subject to little attention

The challenges

- Main problems of face verification over age progression:
  - Biometric changes over years:
    - Facial texture: e.g. wrinkles
    - Shape: weight gain
    - Facial hair: mustache or beard
    - Presence of glasses
    - Scars

  - Changing in the image acquisiton technique and environment:
    - Illumination
    - Image quality: caused by using different cameras
    - Saturation: when converting nondigital photos
    - Changes in pose: not an issue with biometric image sets

Previous approaches

- **Generative** methods:
  - **Concept**: Transform one image to have the same age as the other or transform both to reduce aging effects
  - Age estimation & age simulation
  - Most generative methods require additional information such as **age** or **landmark points**

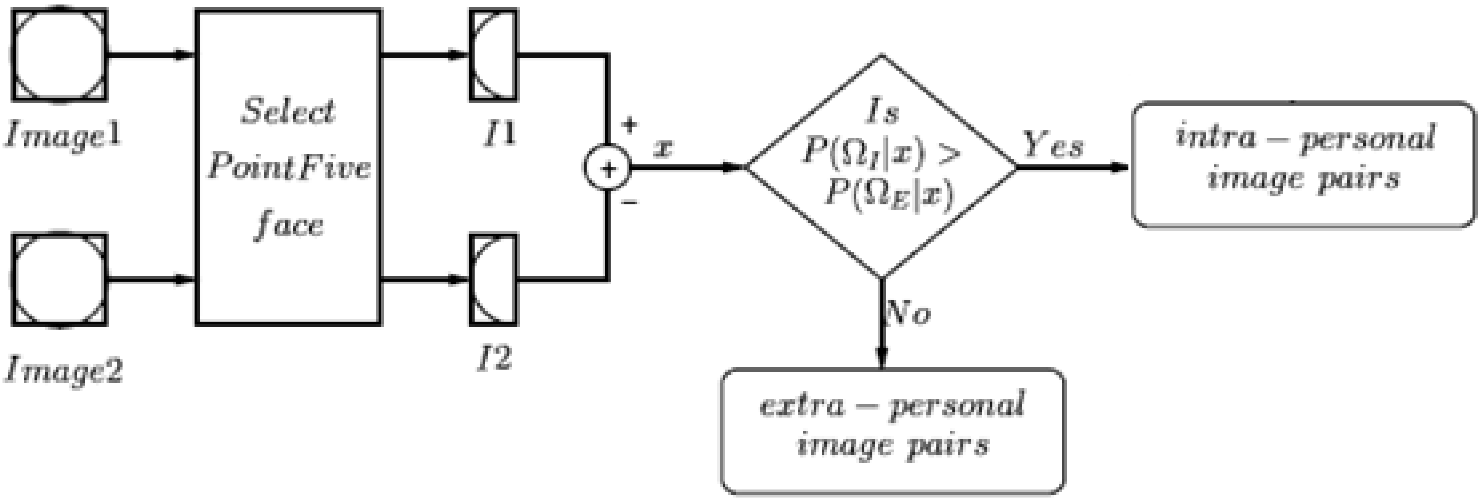
- **Discriminative** methods:
  - **Concept**: As opposed to generative methods, these methods do not allow one to generate samples from the joint distribution
  - Avoid explicit **age modeling**
  - Concentrate on deriving **age-invariant signatures** from faces
  - Age information is not required
  - For tasks such as **classification** discriminative models usually yield better results

Previous approaches – Examples (1)

- Lanitis *et al.*, “Toward automatic simulation of aging effects on face image”:
  - **Generative** method
  - Uses a **statistical model** to capture the variation of facial shapes over age progression
  - The model is then applied on image sets for **age estimation** & **face verification**
  - Simulation of age effects **examples**: (1) - original image; (2) – age-transformed image; (3) – the same person, at the target age

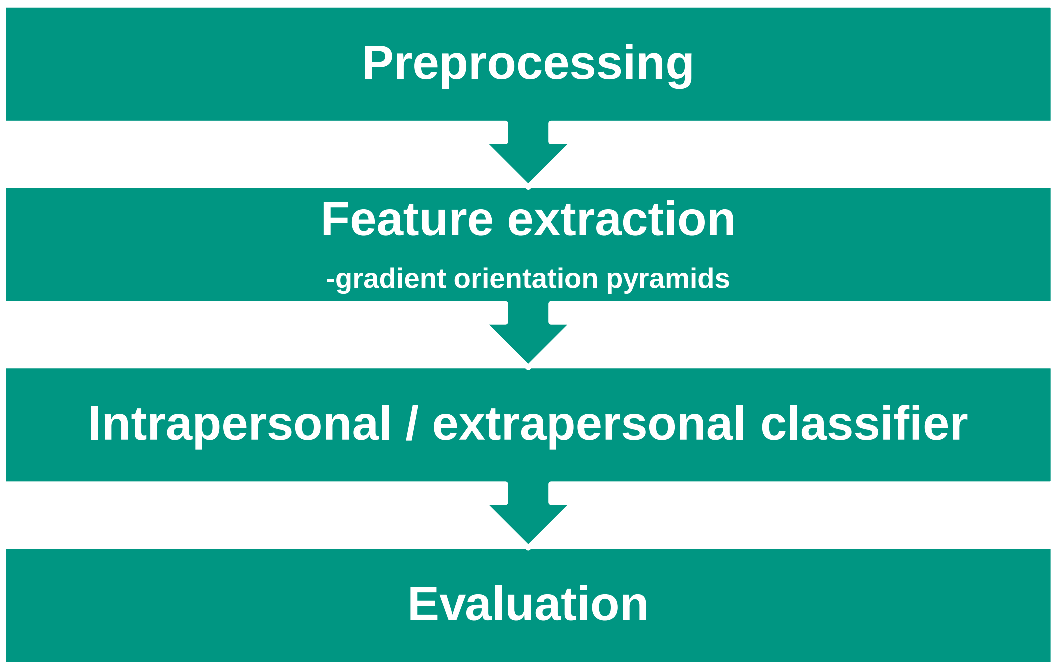
Previous approaches – Examples (2)

- Ramanathan and Chellappa, "Face verification across age progression"
  - **Discriminative** method
  - Uses a half face (PointFive face) to tackle illumination variations
  - **PointFive Face**: better illuminated half of a frontal face (assuming symmetry)
  - Combines **eigenspace** techniques and a **Bayesian model** to capture the intrapersonal and extrapersonal features



The new approach

- Ling, Soatto, Ramanathan and Jacobs, “Face Verification Across Age Progression Using Discriminative Methods”:
  - **Discriminative** method
  - Features are extracted using **gradient orientation pyramids** (GOPs) and classification is made using **support vector machine** (SVM)



Preprocessing & Feature extraction

- Preprocessing:
  - alignment by eye labels
  - cropping with an elliptic region
  - reduce image size
- The feature vector $x = F(I_1, I_2)$ is extracted from the image pair (I_1, I_2) through a **feature extraction function** $F : I \times I \rightarrow R^d$
- *F* relies on **GOP** (gradient orientation pyramids)
  - **GOP** is a gradient-based approach, similar to SIFT (scale invariant feature transfer) and HOC (histogram of oriented gradients)
- **Motivation**:
  - gradient orientation (GO) of each channel of human faces is **robust under age progression**
  - GO is **robust to illumination changes**
  - GOP discards gradient magnitudes and uses only orientations = significant improvement of result

Gradient Orientation Pyramids (1)

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- Given an image *I(p)*, where *p=(x,y)* denotes pixel location, we define the **pyramid of *I*** as:

$$P(I) = \{I(p;\sigma)\}_{\sigma=0}^{s}$$

with

$$I(p;0) = I(p)$$

$$I(p;\sigma) = [I(p;\sigma-1) \otimes \Phi(p)] \downarrow_2$$

- $\sigma = (1, ..., s)$ and s = the number of pyramid layers
- $\phi(p)$ – the Gaussian kernel (standard deviation of 0.5)
- $\otimes$ – the convolution operator
- $\downarrow_2$ – half size downsampling

Gradient Orientation Pyramids (2)

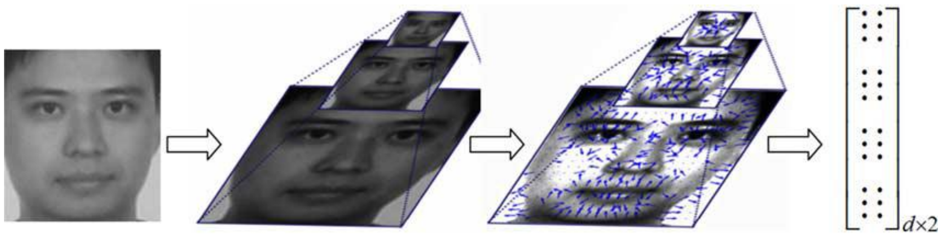
- The **GO** at each scale *σ* is defined by its **normalized** gradient vectors at each pixel:

$$g(I(\mathrm{p};\sigma)) = \begin{cases} \frac{\nabla(I(\mathrm{p},\sigma))}{|\nabla(I(\mathrm{p},\sigma))|}, & \text{if } |\nabla(I(\mathrm{p},\sigma))| > \tau \\ (0,0)^\top, & \text{otherwise} \end{cases}$$

  - τ - threshold for dealing with “flat” pixels
- Consequently, the **GOP** of *I* is defined as:

$$G(I) = stack(\{g(I(p;\sigma))\}_{\sigma=0}^{s}) \in \Re^{d\times 2}$$

  - the *stack* function – used for stacking GOs of all pixels across all scales
  - *d* – the total number of pixels



(a) (b) (c) (d)

Comparing GOPs

- Difference feature vector $x = F(I_1, I_2)$ of an image pair (I_1, I_2) equals to the **cosines of the difference between GOPs at all pixels**:

$$x = F(I_1, I_2) = (G_1 \bullet G_2)\begin{bmatrix} 1 \\ \\ 1 \end{bmatrix}$$

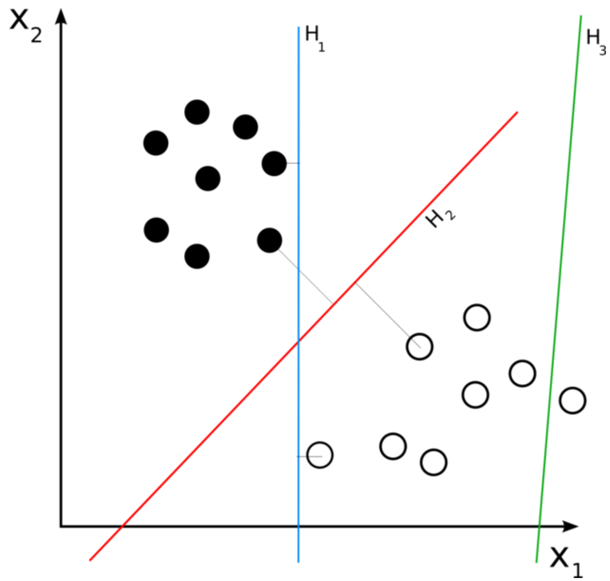
where "•" – the element-wise product

Support Vector Machine Classifier

- The **SVM** divides the feature space into two classes: **intrapersonal** and **extrapersonal**; the boundries are set using the following equation:

$$\sum_{i=1}^{N_s} \alpha_i y_i K(s_i, x) + b = \Delta$$

N_s – the number of support vectors
s_i – the *i*-th support vector
Δ – trade off the correct reject rate (CRR) and correct acceptance rate (CAR)
K – kernel function



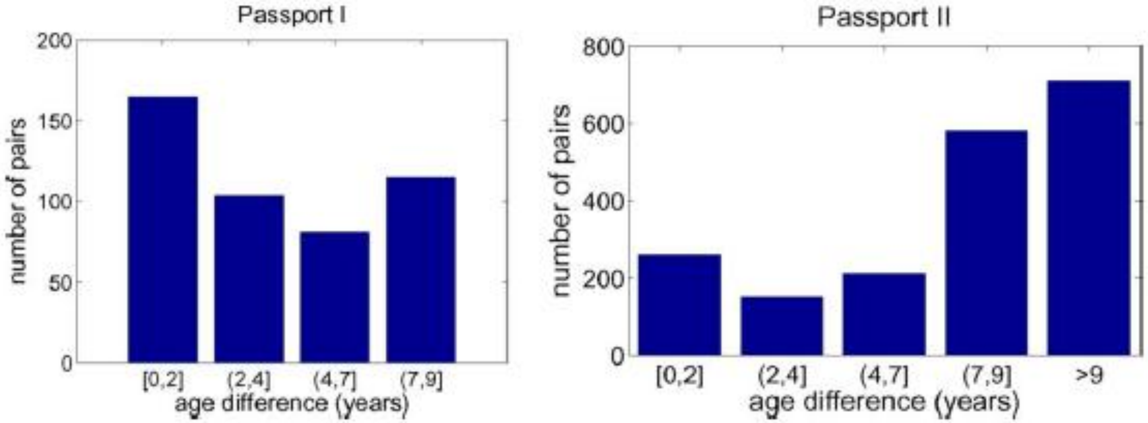
- The gaussian kernel is applied to the extracted feature *x* to be used with the SVM framework:

$$K(\mathbf{x}_1, \mathbf{x}_2) = \exp(-\gamma|\mathbf{x}_1 - \mathbf{x}_2|^2)$$

Experiments & Results (1) – Datasets

- Two passport databases: **Passport I** and **Passport II**:
  - Passport I: **452** intrapersonal & **2251** randomly generated extrapersonal image pairs
  - Passport II: **1824** intrapersonal & **9492** randomly generated extrapersonal image pairs

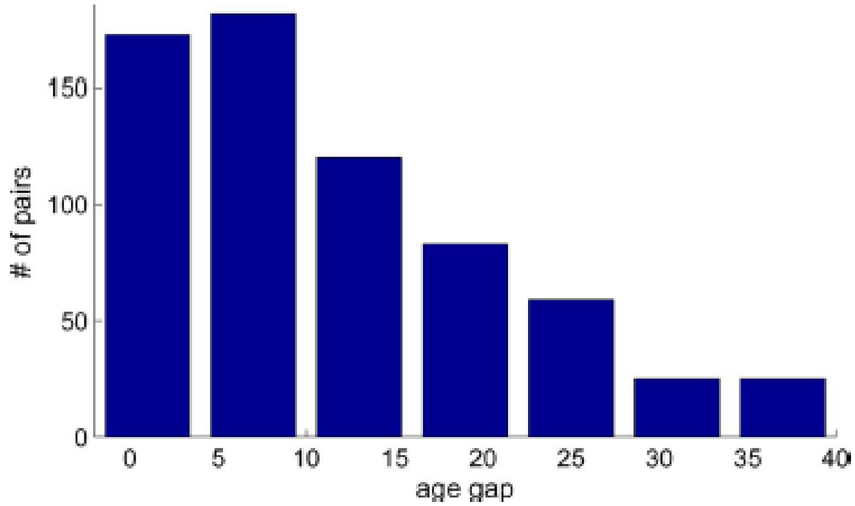
Dataset	# intra pair	mean age	std. age	mean age diff.	std. age diff.
Pass. I	452	39	10	4.27	2.9
Pass. II	1824	48	14.7	7.45	3.2



Experiments & Results (2) – Datasets

- The **FGnet** database:
  - Contains **1002** images from **82** subjects over large age ranges
  - The experiment uses pictures taken **above the age of 18** and roughly frontal faces

# subject	# intra pair	mean age	std. age	mean age diff.	std. age diff.
62	665	29.5	11.3	12.3	9.7



Experiments & Results (3) – Evaluation

- **Metrics**:
  - The **correct reject rate** (CRR):

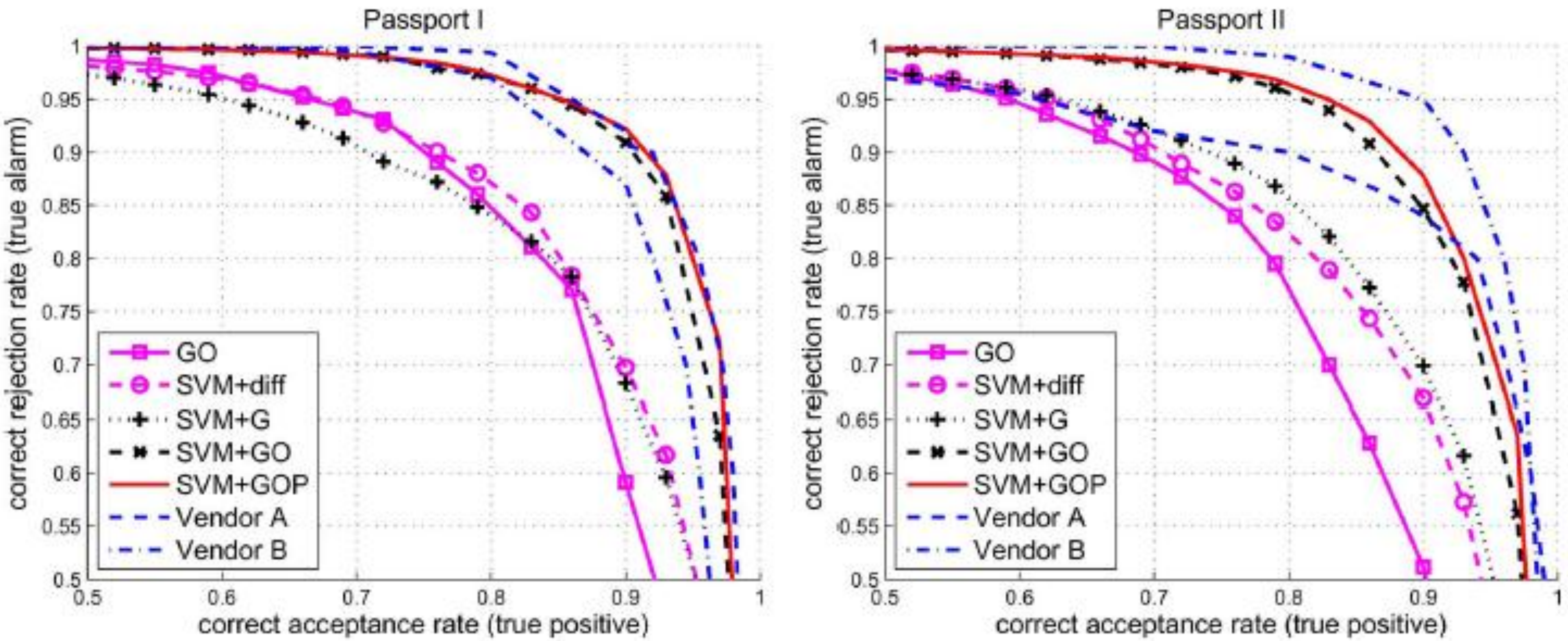
$$\text{CRR} = \frac{\#\text{correctly rejected extra-personal pairs}}{\#\text{total extra-personal pairs}}$$

  - The **correct acceptance rate** (CAR):

$$\text{CAR} = \frac{\#\text{correctly accepted intra-personal pairs}}{\#\text{total intra-personal pairs}}$$

  - The **equal error rate** (EER): the error rate when a solution takes the same CAR and CRR
- **Evaluation**:
  - based on CRR-CAR curves
  - three-fold cross validation
  - only low-res gray images are used for the presented approaches

Experiments & Results (4) – Passport I + II



- (1) SVM+GOP: proposed in this paper
- (2) SVM+GO: uses only the GO at the original scale
- (3) SVM+G: uses the gradient itself, rather than the GO
- (4) SVM+diff: proposed by Phillips
- (5) GO: proposed by Chen, Belhumeur and Jacobs
- (6) *l_2*: uses the *l_2* norm to compare two normalized images
- (7) Bayesian + PointFive Face
- Two commercial systems: *Vendor A* and *Vendor B*

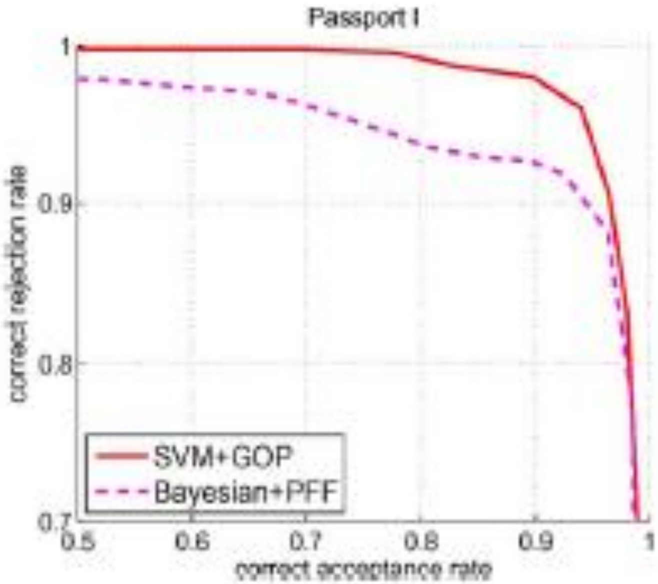
Experiments & Results (5) – Passport I + II

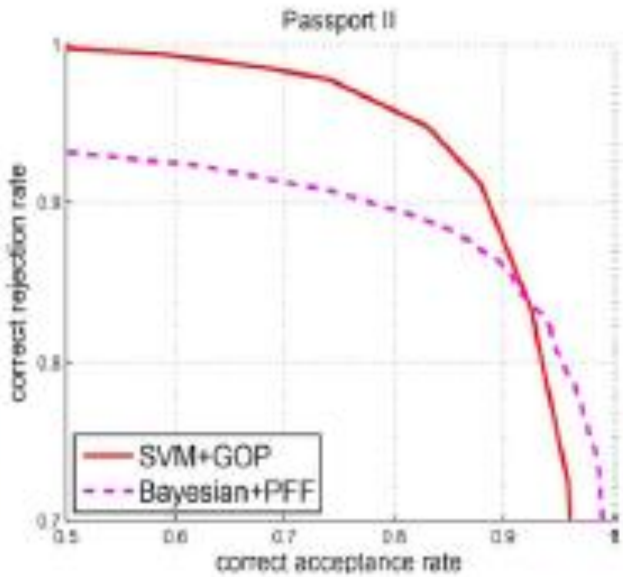
- **Equal Error Rate**:

	GO [6]	SVM+diff [27]	SVM+G	SVM+GO	SVM+GOP	Vendor A	Vendor B
Pass. I	17.6%	16.5%	17.8%	9.5%	8.9%	9.5%	11.5%
Pass. II	20.7%	18.8%	17.4%	12.0%	11.2%	13.5%	8.0%

SVM+GOP	Bayesian [30]
5.1%	8.5%
10.8%	12.5%

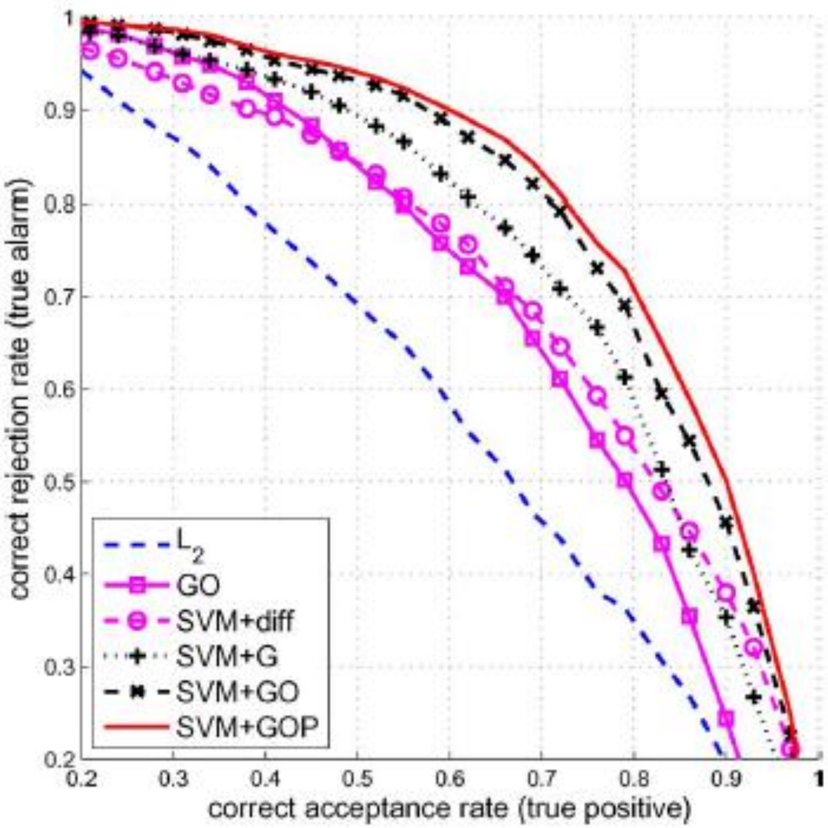
- Comparison between **SVM+GOP** and **Bayesian+PointFive Faces**:

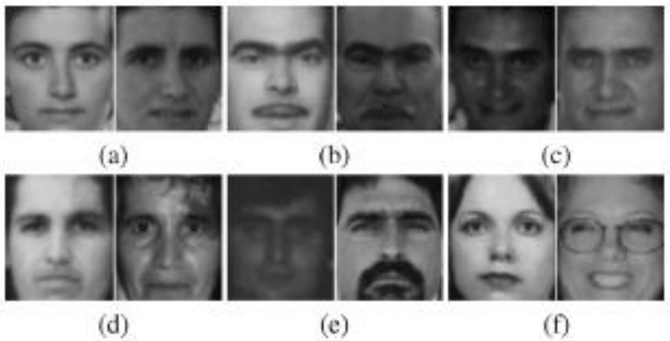




Experiments & Results (6) – FGnet database

- **Challenges**: large age gaps (up to 45 years) & limited number of subjects (making learning difficult)





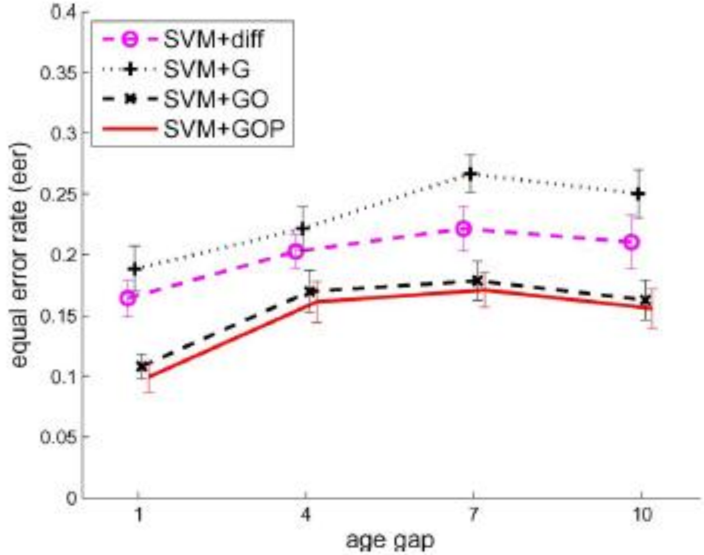
(a), (b), (c) – correctly accepted intrapersonal pairs
(d), (e), (f) – inccorectly rejected intrapersonal pairs

Age difference:

(a) 18 years; (b) 31 years; (c) 7 years
(d) 35 years; (e) 23 years; (f) 32 years

Observations (1)

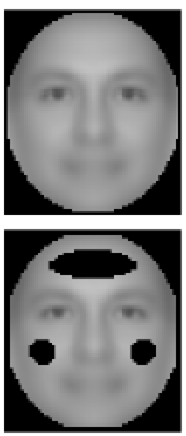
- Face verification complexity becomes **saturated** after the age gap is larger than four years (but not longer than 10 years)
  - Experiment on Passport II, trained with 80 random intra and 80 random extra pairs:

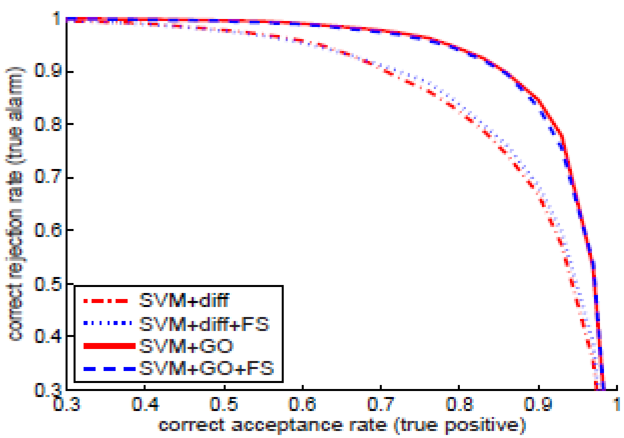


- Verification on **children faces** is much harder than on adults
  - The alignment problem

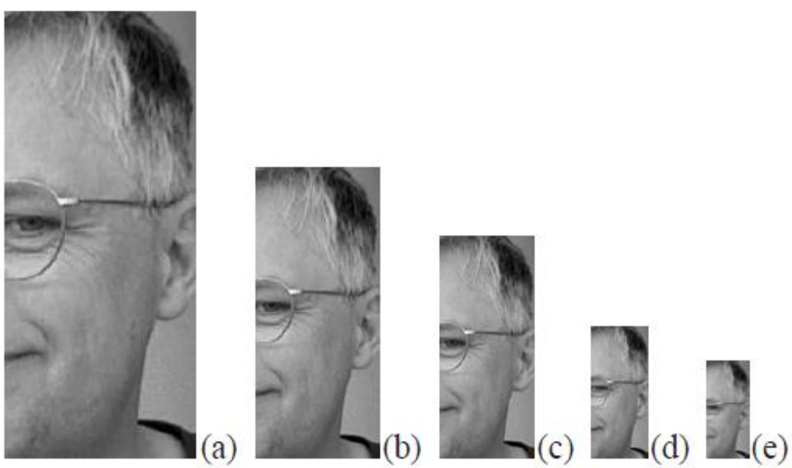
Observations (2) – Wrinkle related features

- Important factors for age perception
- Hardly perceptible with low-res images
- Appear mostly on forehead and cheeks: irrelevant areas for face recognition
- **Conclusion**: wrinkles can be ignored (e.g. through manually adjusted masks or automatic feature selection)





+FS: with feature selection mask



Conclusion

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- SVM+GOP outperforms commercial systems on most tests, which are usually very well tuned
- Advantages:
  - **discriminative method**: requires no prior age information and doesn’t rely on age estimation & simulation algorithms
  - GOP is insensitive to illumination changes
  - GOP is robust across age progression
  - good performance, compared to other existing algorithms

Questions?

Sources

- **Bibliography:**

  - Ling, Soatto, Ramanathan and Jacobs – "Face Verification Across Age Progression Using Discriminative Methods"
  - Ling, Soatto, Ramanathan, Jacobs – "A Study of Face Recognition as People Age"
  - Lanitis *et al.* – "Toward automatic simulation of aging effects on face image"
  - Ramanathan, Chellappa – "Face verification across age progression"
  - Abate, Nappi, Riccio, Sabatino – "2D and 3D face recognition: A survey"

- **Images**:
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  - http://www.artofobama.com/wp-content/uploads/2009/01/obama-age.jpg
  - http://morph.cs.st-andrews.ac.uk/Transformer/
  - http://en.wikipedia.org/wiki/File:Svm_separating_hyperplanes.png