Recunoasterea Fetelor Umane

Interfata vizuala om-masina

Corneliu Florea

Cuprins

1. Problema recunoasterii
2. Normalizarea fetelor
3. Solutii :
   a. Recunoasterea fetelor pe baza LBP
      - Texture Unit
      - Local Binary Pattern
      - Utilizarea LBP pentru recunoasterea fetelor
   b. Recunoasterea fetelor prin analiza imaginilor 3D
      - De ce 3D
      - Recunoasterea in 3D
   c. Recunoasterea utilizand retele convolutionale adanci

Biometrica

- **Biometrica** – stiinta care se ocupa cu recunoasterea automata a indivizilor pe baza trasaturilor biologice si comportamentale
- **Sistem biometric** – un sistem de recunoastere care identifica o persoana prin autentificarea unor trasaturi bilogice si comportamentale specifice
- **Antropometrie** – Metode de masura ale corpului uman si partilor lui
- Oamenii se identifica prin:
  - Ceva ce au (documente de identitate)
  - Ceva ce stiu (parole)
  - Ceva ce sunt (cum arata)

[Belhumeur]

Biometrica

- Identificarea biometrica a oamenilor se face prin:

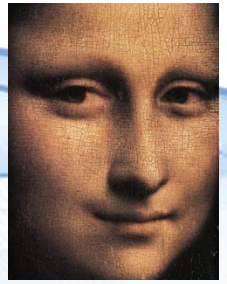
Retina – fiecare ochi are o retea unica de vase de sange





Amprente – masura judiciara arhicunoscuta

Fata



http://www.knowledgebase-script.com/demo/article-572.html

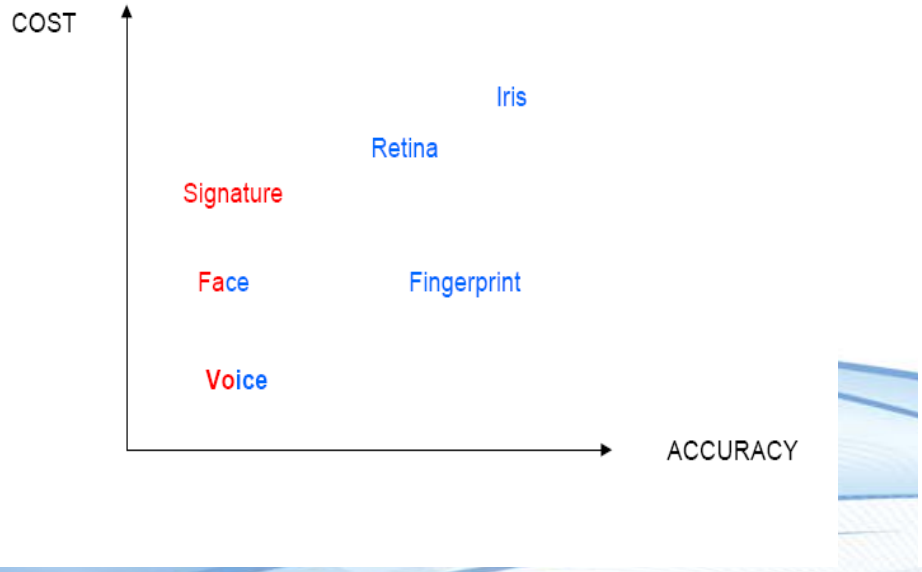
[Belhumeur]

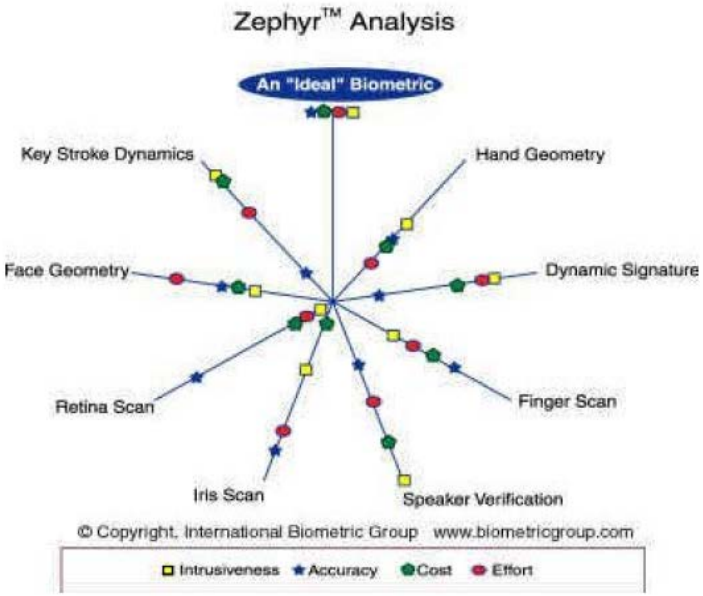
Masuri biometrice “soft”

- Exista masuri care dau indicii despre persoana din spate:
  - Postura
  - Varsta

Comparatie intre tehnicile biometrice

Diferitele metode biometrice difera intre ele prin cost, acuratete, efort





[Belhumeur]

Recunoasterea fetelor

Doua aspecte:

1) Identificare

- Se raspunde la intreabarea “Cine este X?”
- Este realizat de un sistem care implementeaza
  - cautare “unul la multi”

2) Verificare

- Se raspunde la intrebarea “Este acesta X?”
- Este realizat de un sistem care implementeaza
  - cautare “unul la unu”

Recunoasterea fetelor

- Este probabil caracteristica biometrica cea mai utilizata in mod natural de catre oameni
- Tehnica non-intruziva care este acceptata de catre oameni ca o caracteristică biometrica
- Subiect de cercetare intensivă de peste 25 de ani

- Aplicatii:
  - Cautare de persoane in domeniul juridic sau pentru securitate
  - Autentificare
  - Personalizare automata

Recunoasterea fetelor de catre oameni

- Omul recunoaste fete comparand una noua cu una memorata si estimand gradul de similaritate
- Se pare ca recunoasterea fetelor este realizata de o parte specifica a creierului uman
- Procesul de recunoastere se bazeaza atat pe aspecte particulare cat si pe forma in ansamblu
- Memoria fetelor este dependenta de perspectiva
- Recunoasterea fetelor se face in paralel cu recunoasterea expresiilor
- Oameni recunosc mai bine persoane din propria rasa

Recunoasterea fetelor de catre oameni

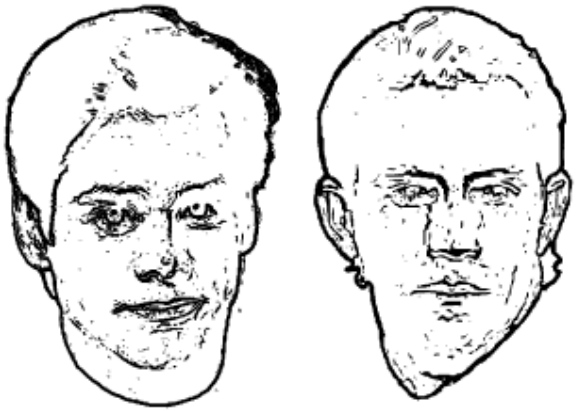
- [Sinha] studiaza intensiv recunoasterea feteor de catre oameni si construieste exemple pentru a demonstra puterea acestui sistem



Putem recunoaste fete la rezolutie foarte mica

[Sinha]

Recunoasterea fetelor de catre oameni



Informatia de contur nu este foarte utila:

Jim Carey, Kevin Costner



Compresia (scalarea) brutala permite in continuare recunoasterea

[Sinha]

Recunoasterea fetelor de catre oameni



- [Sinha] foloseste acest exemplu pentru a ilustra dificultatea gasiri unei masuri potrivite de similaritate
- Cele doua imagini exterioare sunt ale aceleiasi persoane, in timp ce cea din centru este o persoana diferita. Dar cam orice masura de similaritate va spune altceva.

[Sinha]

Variatia iluminarii : IACS!



Interior



Exterior

[Belhumeur]

Dificultati : variatia imaginilor

Termen scurt

Expresia



Postura



Iluminarea



Termen lung

- Par facial
- Machiaj
- Ochelari
- Frizura
- Piercing
- Imabatranirea

[Belhumeur]

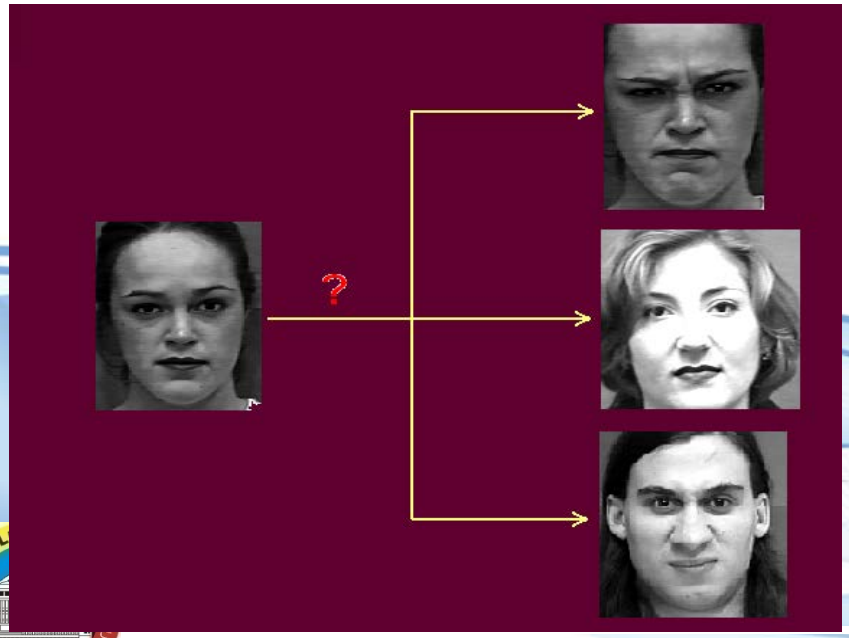
Necesitati ale recunoasterii

- Pentru a obtine rezultate bune in recunoasterea fetelor:
  - Achizitie foarte restrictiva – poze de cazier
  - Normalizarea fetelor – aducerea fetelor la un standard de :
    - Iluminare – uniforma pe toata suprafata fetei
    - Pozitie - se rotesc, scaleaza si translateaza fetele astfel incat sa se potriveasca ochi si gura pe aceleasi pozitii
    - Expresie – neutra
  - Utilizarea de metode invariante la posibilitatile de variatie

Solutie generala

Identificare : Se minimizeaza o masura de similaritate intre poza interogata sau o transformare a ei si reprezentantii fiecarei clase invatate

Verificare : Se calculeaza distanta pana la referinta si se compara cu un prag



Ce masuri de similaritate stim?

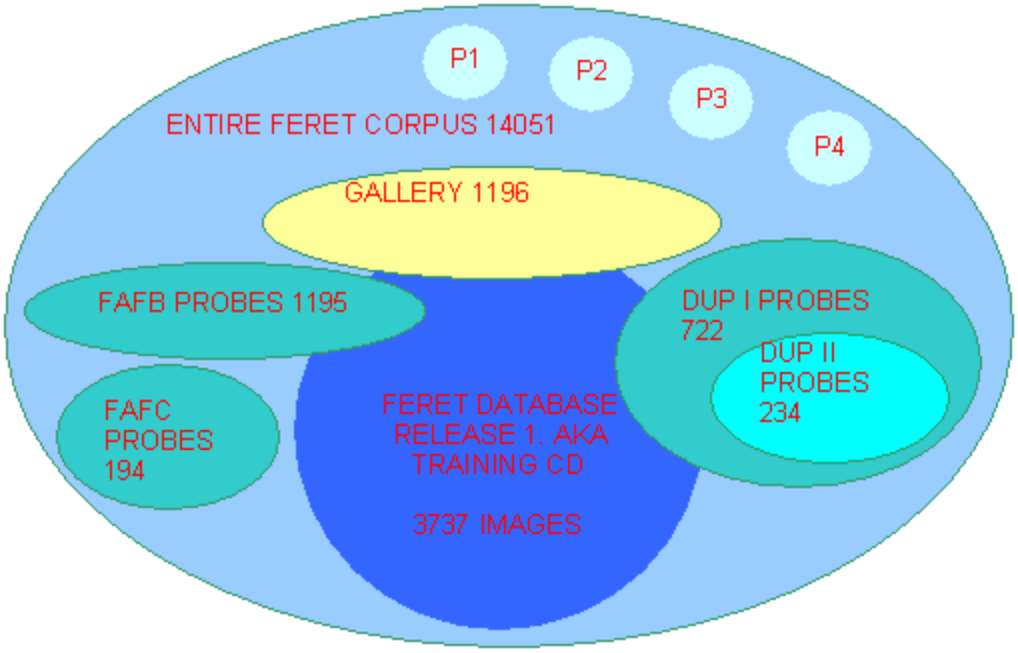
- Distante spatiale – norme
- Distante unghiulare
- Corelatie
- Distante intre functii
- ??

Imagini din baza Cohn-Kanade

Evaluarea performantelor

FERET database:

- Baza de date publica (la cerere) pentru evaluarea recunoasterii
- Contine imagini a 1196 de persoane cu pana la 5 poze per individ
- Competitie deschisa
- Rezultate publice pentru algoritmii cunoscuti



Normalizarea FERET

Pentru normalizare este necesara cunoasterea pozitiei ochilor

- Imaginea este rotit pentru a alinia ochii.
- Imaginea este scalata pentru a face distanţa dintre ochi constanta. Imaginea este, de asemenea, trunchiată astfel incat sa contina doar fata.
- Se aplică o mască pentru a anula pixeli din afara unui oval ce contine o fata tipica. Ovalul este generat analitic.
- Se egalizeaza histograma pentru a netezi distribuţia valorilor de gri a pixelilor din oval
- Imaginea este normalizata astfel incat pixelii din oval sa aiba medie zero si deviatie standard 1.

Local Binary Pattern

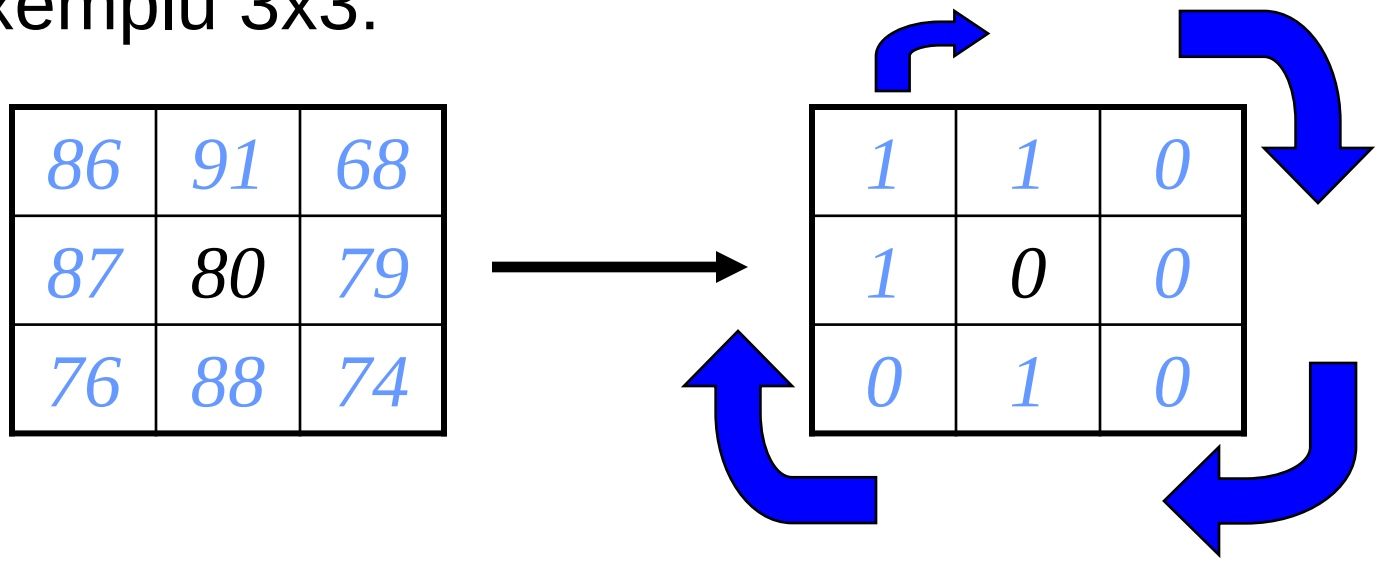
- Local Binary Pattern (LBP) este un descriptor de textura care codifica primitivele locale (muchii, curbe, pete, zone uniforme) intr-o histograma de trasaturi
- Se defineste pe o ferestra 3x3 in care
  - Valoarea curenta este g_0
  - Valorile din vecinatate sunt $g_1,\ldots, g_8$:
- Fereastra rezultanta este:

g_1	g_2	g_3
g_4	g_0	g_5
g_6	g_7	g_8

$$e_i = \begin{cases} 0, & g_i < g_0 \\ 1, & g_i \geq g_0 \end{cases}$$

Local Binary Pattern

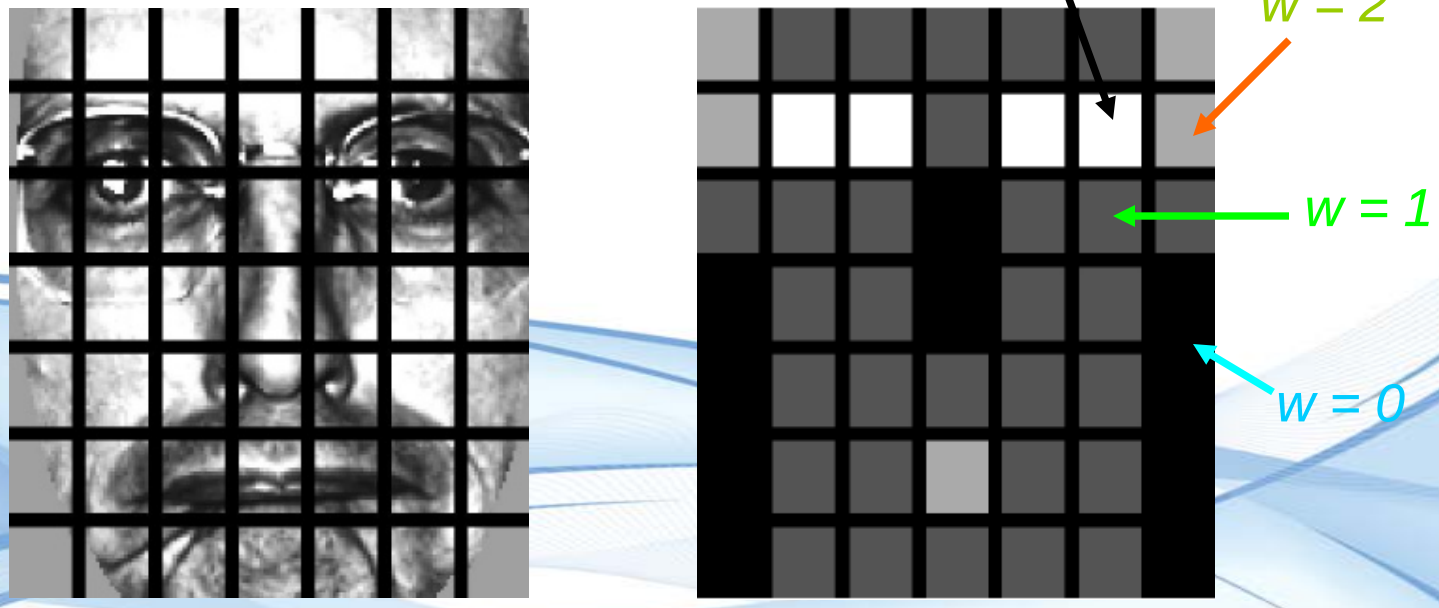
- Exemplu 3x3:



- Cele 8 valori calculate formeaza cei 8 biti ai unui octet:
  - Se incepe din (0,0) si se parcurge circular
    - Se fixeaza directia
    - 11000101

Ponderarea blocurilor

- Blocurile sunt ponderate
  - Ochii si gura conteaza mai mult cand se face diferentierea intre persoane
  - Zonele uniforme cele mai putin semnificative



Similaritatea - divergenta KL

Cum verificam carei fete ii corespunde?

Trebuie verificata **similaritatea** intre doua histograme

Masuri de similaritate intre histograme :

- Divergenta Kullback – Leibler (entropia relativa) este:

$$D_{KL}(P \parallel Q) = \sum_{x} P(x) \log \frac{P(x)}{Q(x)}.$$

Se arata ca :

$$D_{KL}(P||Q) \geq 0$$

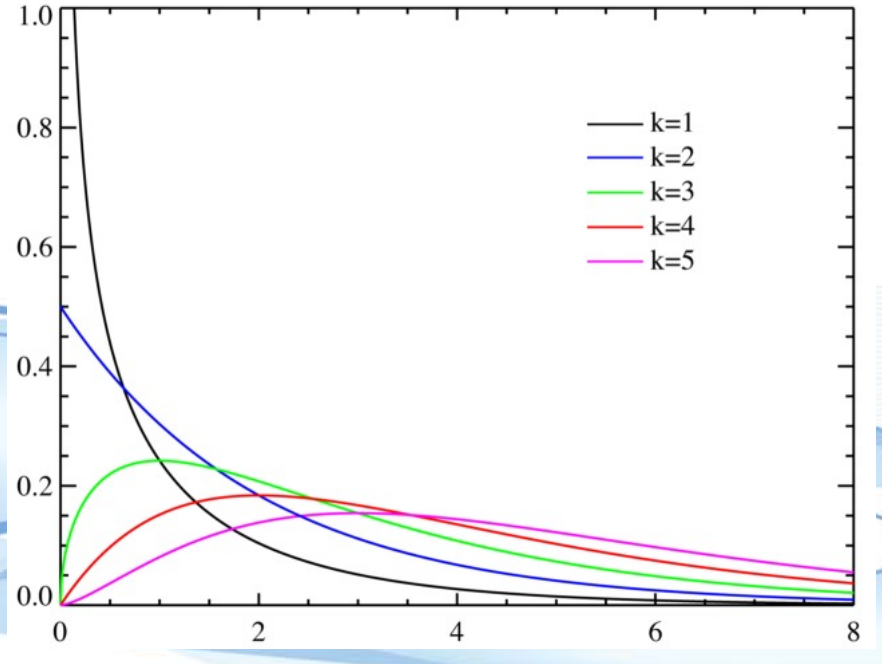
Cu egalitate daca $P(x) = Q(x)$

→ Ii va corespunde fetei pentru care divergenta este minima

Similaritatea - legea χ^2

Masuri de similaritate intre histograme :

- Legea χ^2 (chi square)
  - In fapt χ^2 este un test daca un set de date este distribuit conform unei legi cunoscute
  - Legea χ^2 reprezinta distributia unei sume de patrate de v.a. gaussiene independente



Similaritatea - legea χ^2

Testul χ2 pentru verificarea unei distributii:

- Se partioneaza datele in *M* intervale
- Se determina probabilitatile fiecarui interval
- Se alege pragul testului: *α* cuantila superioara (la 0.05), notat x_α
- Se formeaza valoarea de test : $z = \sum_x \frac{(m_x - NP_x)^2}{NP_x}$.

- Daca $z > x_\alpha$, atunci datele sunt distribuite conform legii

Pentru comparare de histograme se cauta valoarea maxima pentru:

$$\chi_w^2(x,\xi) = \sum_{i,j} w_j \frac{(x_{i,j} - \xi_{i,j})^2}{x_{i,j} + \xi_{i,j}}.$$

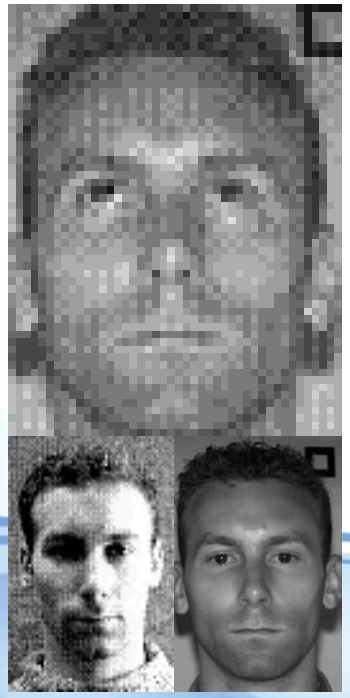
Histograma fetei de referinta

ponderi

Histograma curenta

Face 3D - Limitari pentru recunoasterea in 2D

Eficienta sistemului este dependenta de conditiile de achizitie.



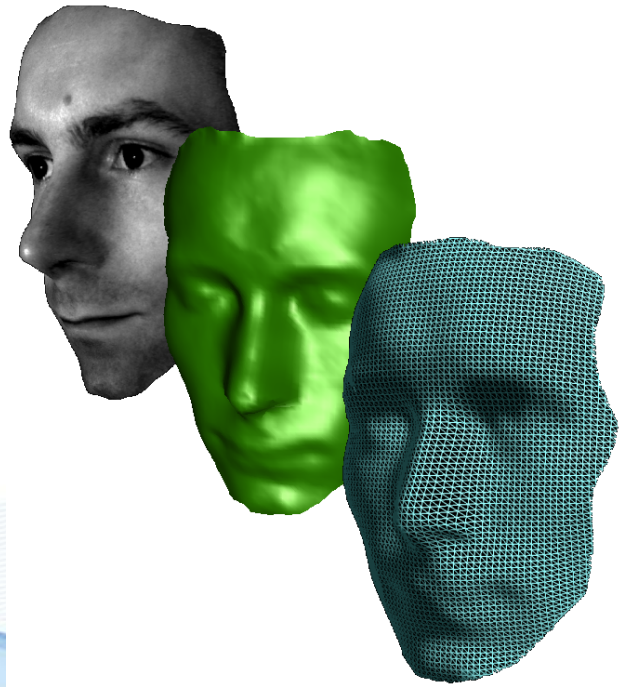
- **Conditiile de iluminare:**
  - Condiţii diferite de iluminare pentru înscriere respectiv interogare.
  - Pot provoaca saturaţia imaginii.
- **Orientarea capului:**
  - Distantele calculate pe caracteristici 2D se distorsioneaza.
- **Calitatea imaginii.**
  - CCTV, Web-cams, etc
- **Expresia faciala**.
  - Modificări în locaţia şi forma caracteristică.
- **Ocluzii Parţiale**
  - Pălării, eşarfe, ochelari etc



Recunoasterea fetelor 3D

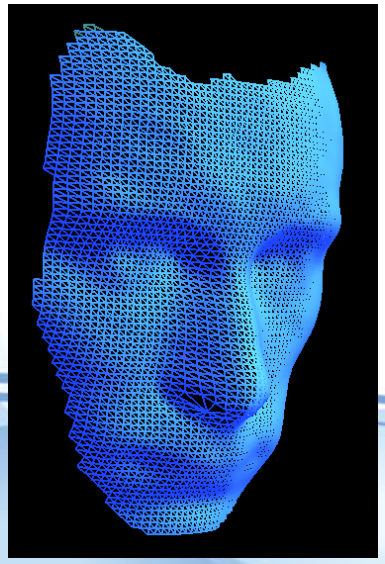
Recunoasterea fetelor prin modelare 3D:

- Achizitie 3D a fetelor umane – noi modele de camere 3D sau prin stereografie
- Construirea unui model 3D si adaptarea lui in functie de imaginea 2D data
- Beneficii:
  - Se utilizeaza informatie geometrica de adancime in loc de culoare si textura
  - Este invarianta la variatia iluminarii
  - Permite rotatii – invarianta la postura
  - Permite scalare – invarianta la zoom



Portrete 3D

- Generate cu ajutorul unei camere stereo
- Suprafata fiecarei fete este reprezentata de ~ 8000 de puncte.
- Pe suprafata se mapeaza textura din imaginea cu tonuri de gri.



Reteaua de puncte



Poligoanele



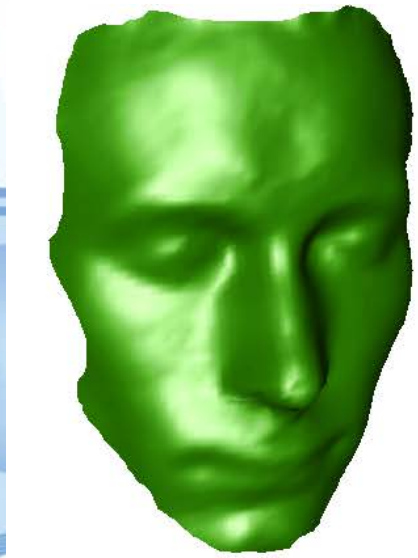
Textura



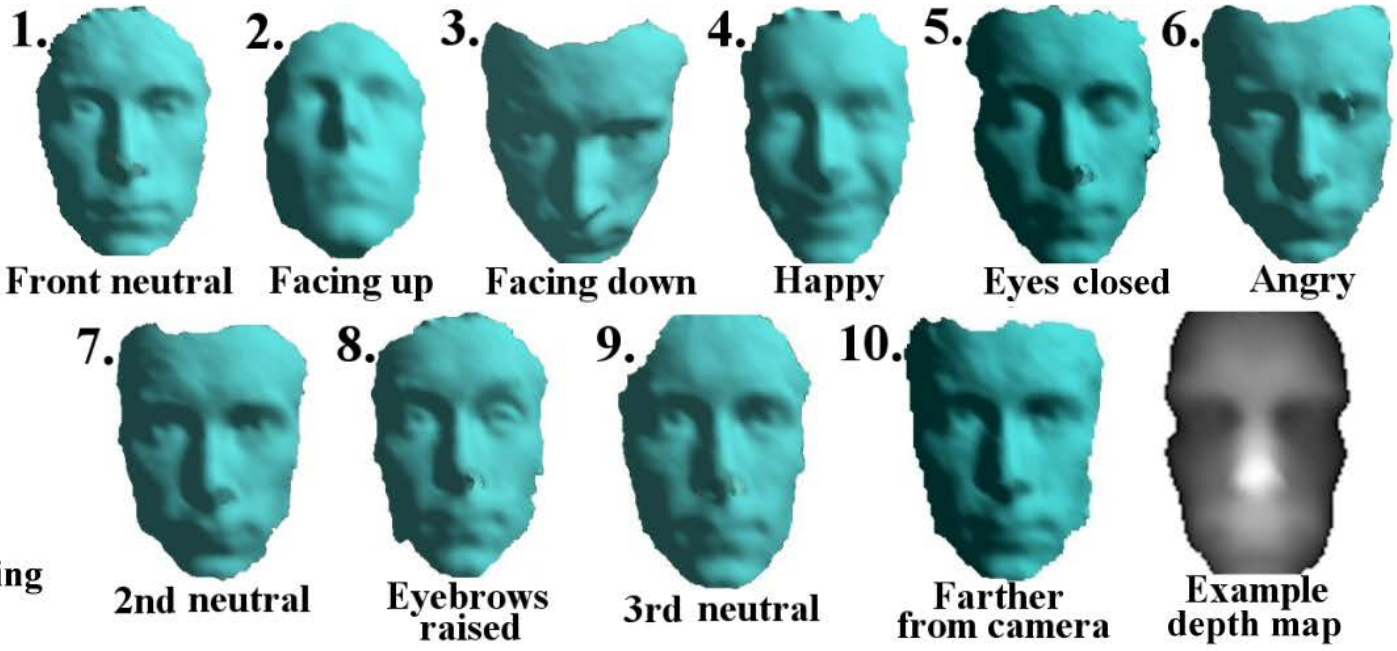
Iluminarea

Baza de date

- Baza de date de la universitatea York
  - 5000 modele de fete a peste 350 de persoane.
  - Variatie mare in raport cu expresia orientarea, sexul, apartenenta etnica, varsta.
- Un subset (1770 modele) este folosit pentru antrenare si testare.
  - 300 modele 3D models a 50 de persone in antrenare
  - 1470 modele 3D a 280 de persoane pentru testare



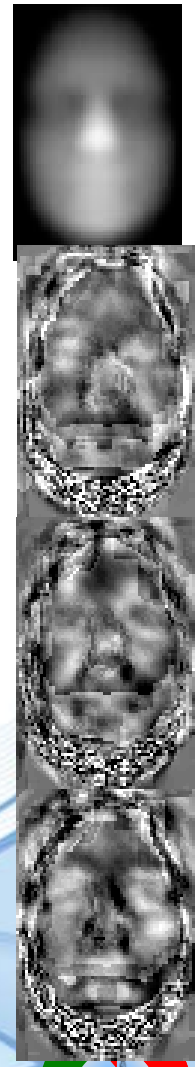
3D face model captured using a stereo vision camera



Fete Fisher pentru 3D

Adaptare a fetelor Fisher (LDA) la date 3D:

- Modelele 3D sunt aliniate frontal
- Modelele 3D se convertesc in harti de adancime
  - Dimensiune 60 x 90 pixeli.
  - Se extrag caracteristici derivate
- Se utilizeaza LDA pentru reprezentare simplificata
- Hartile de adancime sunt comparate pe baza distantei euclidiene sau a distantei *cos*

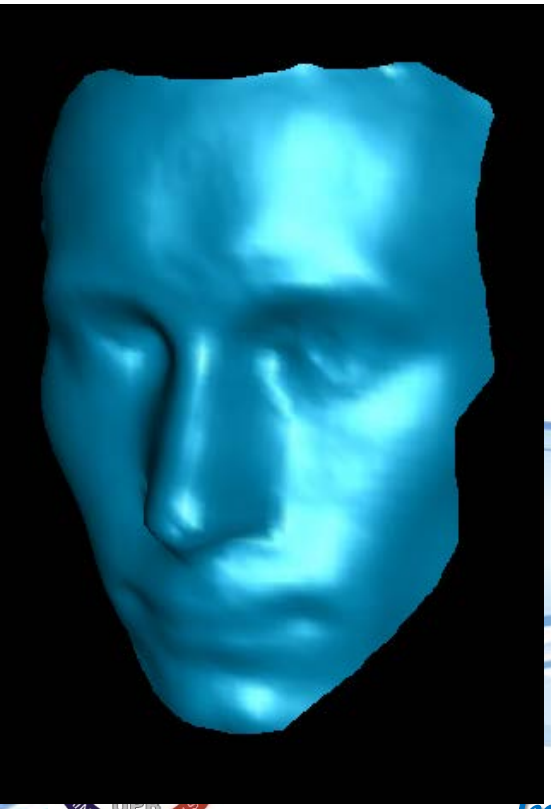


$$d_{Euclid} = \|\Omega_a - \Omega_b\| \qquad d_{\cos} = 1 - \frac{\langle \Omega_a, \Omega_b \rangle}{\|\Omega_a\| \cdot \|\Omega_a\|}$$

[Heseltine]

Caracteristici derivate pentru fete 3D

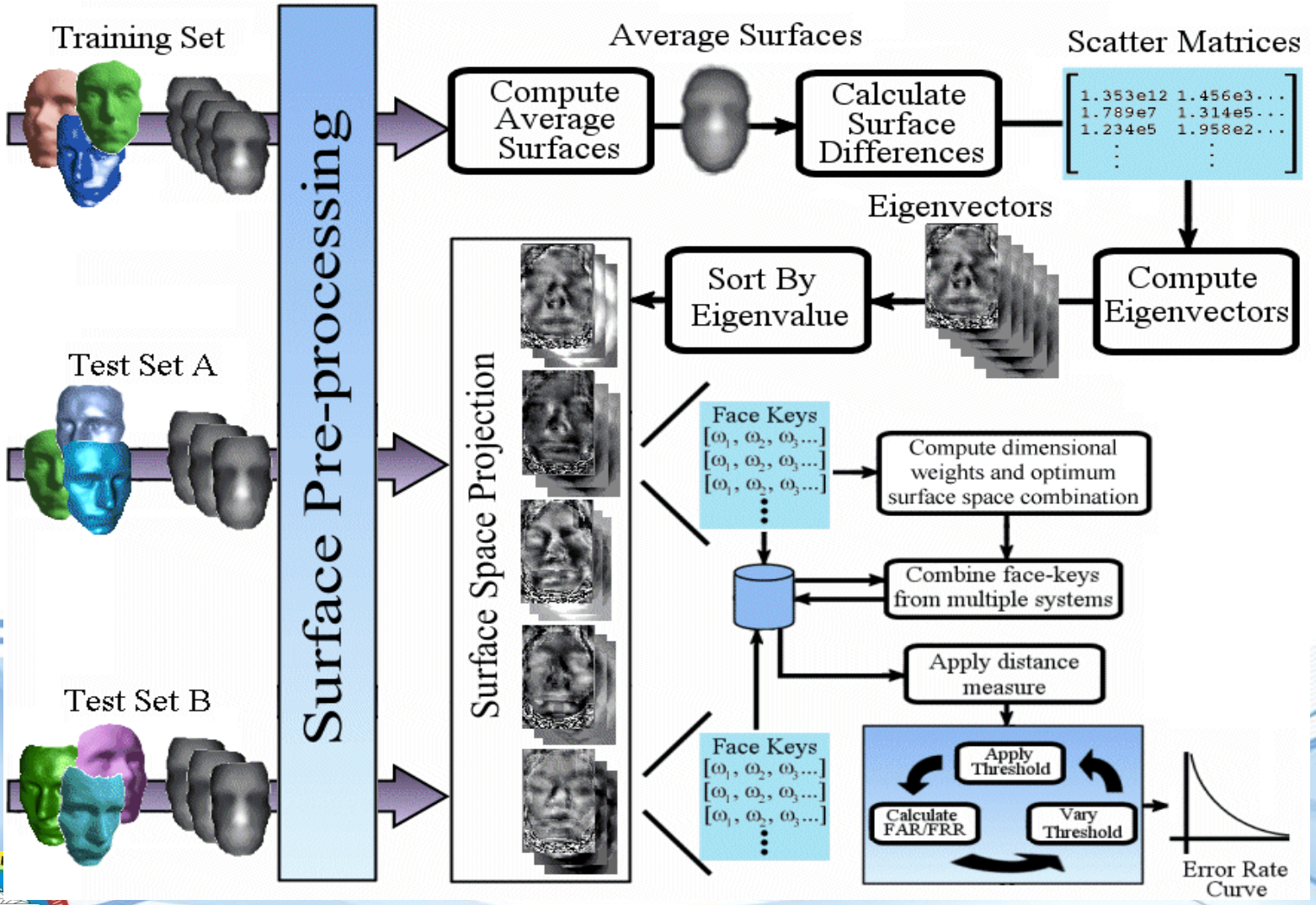
Pe langa harta de adancime se mai adauga 16 caracterizari ale fetei 3D





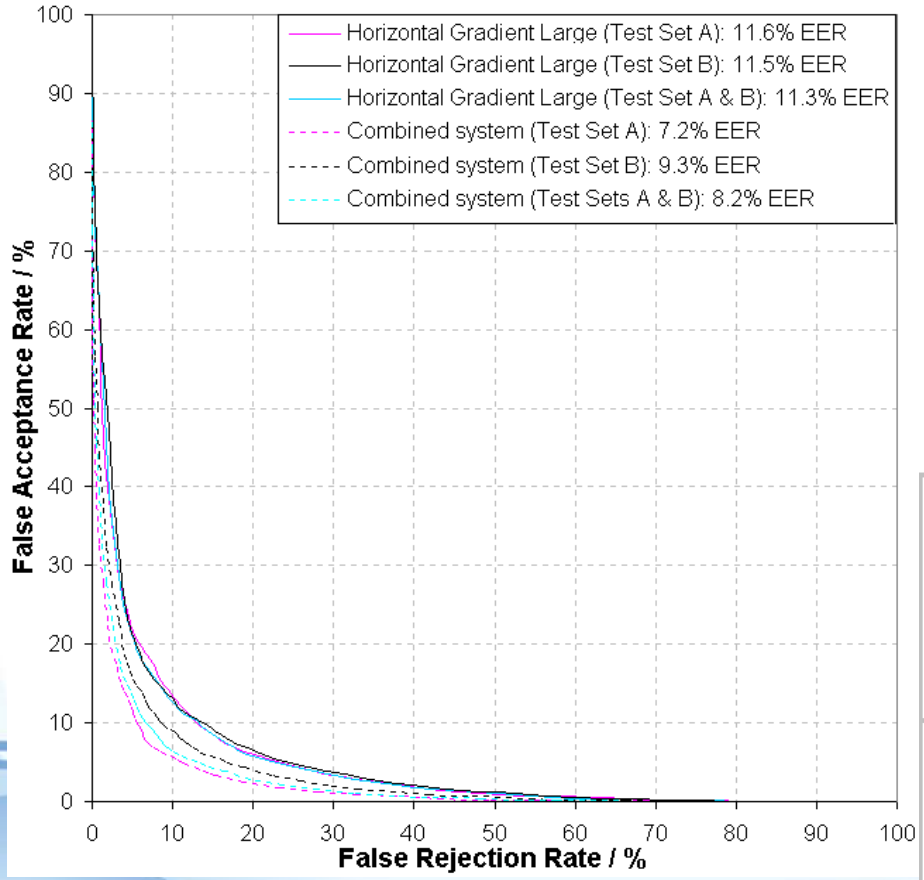
Horizontal Gradient	Vertical Gradient	Horiz. Gradient Large	Vert. Gradient Large
 -1 1	 -1 1	 -1 0 0 0 1	 -1 0 0 0 1
Applies the 2x1 kernel to compute the horizontal derivative	Applies the 1x2 kernel to compute the vertical derivative	Horizontal gradient over a greater horizontal distance	Vertical gradient over a greater vertical distance
Laplacian	**Sobel X**	**Sobel Y**	**Sobel Magnitude**
 0 1 0 1 −4 1 0 1 0	 -1 0 1 -2 0 2 -1 0 1	 1 2 1 0 0 0 -1 -2 -1	
An isotropic measure of the second spatial derivative	Application of the horizontal sobel derivative filter	Application of the vertical sobel derivative filter	The magnitude of Sobel X and Y combined.
Horizontal Curvature	**Vertical Curvature**	**Curvature Magnitude**	**Curve Type**
			
Applies sobel X twice to calculate the 2nd horizontal derivative	Applies sobel Y twice to calculate the 2nd vertical derivative	The magnitude of the vertical and horizontal curvatures	Segmentation of the surface into 8 discreet curvature types
Min Curvature	**Max Curvature**	**Abs Min Curvature**	**Abs Max Curvature**
			
The minimum of the horizontal & vertical curvature values	The maximum of horizontal & vertical curvature values	The minimum of absolute horizontal & vertical curvatures	The maximum of absolute horizontal & vertical curvatures

Procedura de test



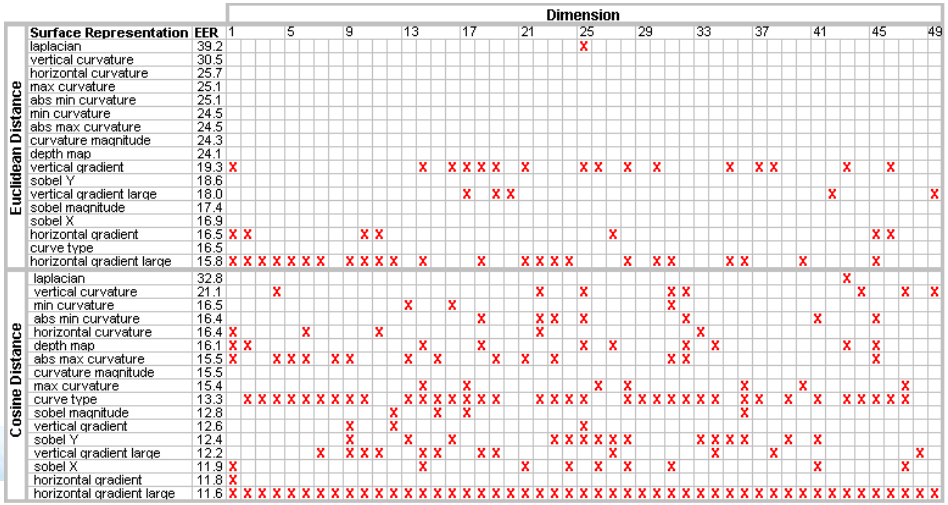
[Heseltine]

Rezultate finale



Dimensiunile relevante din reprezentarile unei singure trasaturi de suprafata sunt incorporate intr-o reprezentare compacta a fetelor 3D

Se foloseste metrica pe baza de distanta *cos*.



8.2% EER pe testul complet (11.3% single)

7.2% EER pe setul de test set redus (11.6% single)

RECUNOASTEREA FETELOR CU RETELE CONVOLUTIONALE ADANCI





Milestone : DeepLearning

- Solutii bazate pe DeepLearning au permis aparitia de solutii care obtin performante mai bune decat omul in conditii standard
  - Conditii non-standard necesita solutii speciale – future
- Au aparut in paralel cu baze mai de date:

  -Exemple:

  - Taigman, Y., Yang, M., Ranzato, M. A., & Wolf, L. (2014). Deepface: Closing the gap to human-level performance in face verification. CVPR Link - https://www.cs.toronto.edu/~ranzato/publications/taigman_cvpr14.pdf
  - Schroff, F., Kalenichenko, D., & Philbin, J. (2015). Facenet: A unified embedding for face recognition and clustering, CVPR Link -https://arxiv.org/pdf/1503.03832v3.pdf
  - Parkhi, O. M., Vedaldi, A., & Zisserman, A. (2015, September). Deep face recognition. In *BMVC* (Vol. 1, No. 3, p. 6).Link: http://cis.csuohio.edu/~sschung/CIS660/DeepFaceRecognition_parkhi15.pdf

Deep face models

- De ce Deep?
- Ipoteza: Modelele de reprezentare faciala se află intr-un spatiu multi-dimensional complex, neliniar și non-convex.
- Abordarea curenta – Deep:
  - Obtinem baze de date mai mari : web-crawling – more faces!
  - Solutia celor de Google / Facebook etc.
  - Hardware mai puternic in sistemele embedded – putem lucra cu modele mai puternice

DeepFace

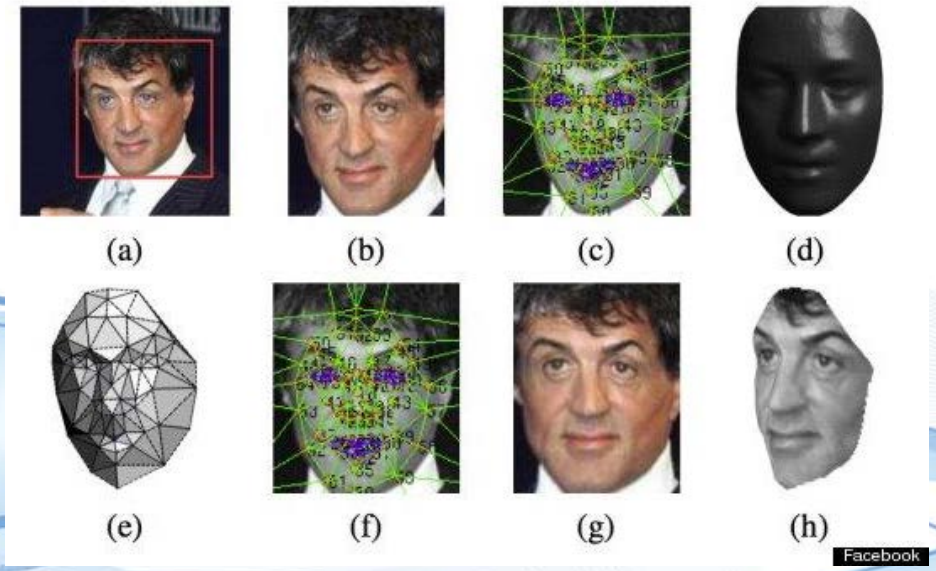
Wolf- 2014



- Modelare 2D/3D si aliniere folosint transformari afine
- Retea convolutionala adanca cu 9 straturi si 120 milioane de parametri

DeepFace- Aliniere

- Se determina punctele cheie (landmark-uri)
- Se construiesc modele 2D/3D ale fetei
- Se aplica o transformare a afina asupra imaginii curent pentru a o aduce la o forma prestabilita (frontal)



http://web.eng.tau.ac.il/deep_learn/wp-content/uploads/2016/11/Face-Recognition-A-Deep-Learning-Approach.pdf

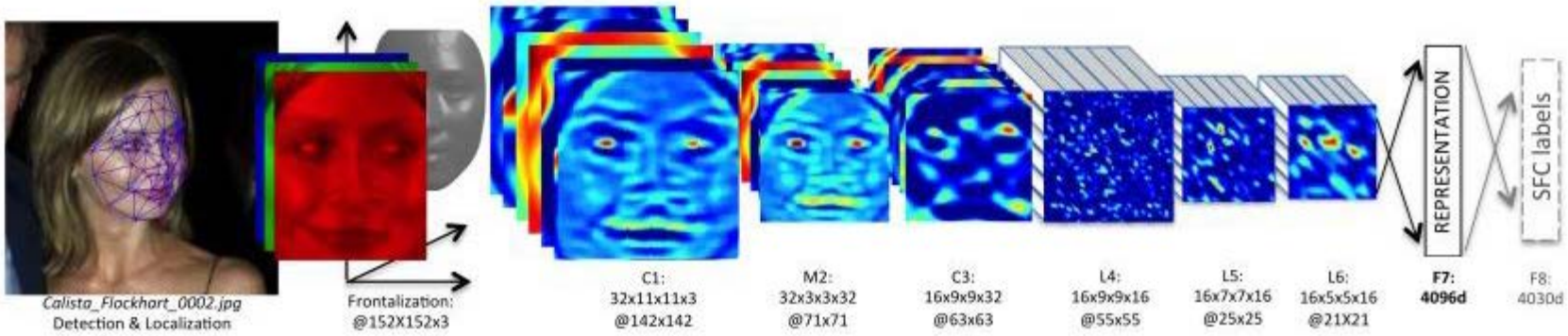
DeepFace- DeepLearning

Reteaua

- Date de intrare: Imagini 3D (RGB) de 152x152 pixeli cu fate
  - pre-rulat face detector
- Retea convolutionala cu 9 straturi
- Include soft max pentru minimizarea “cross entropy”
- Antrenare cu SGD, regularizare cu, Dropout,
- Reducere dimensionalitatii cu ReLU
- Date de iesire: probabilitati pentru k classe

DeepFace -Deep Learning

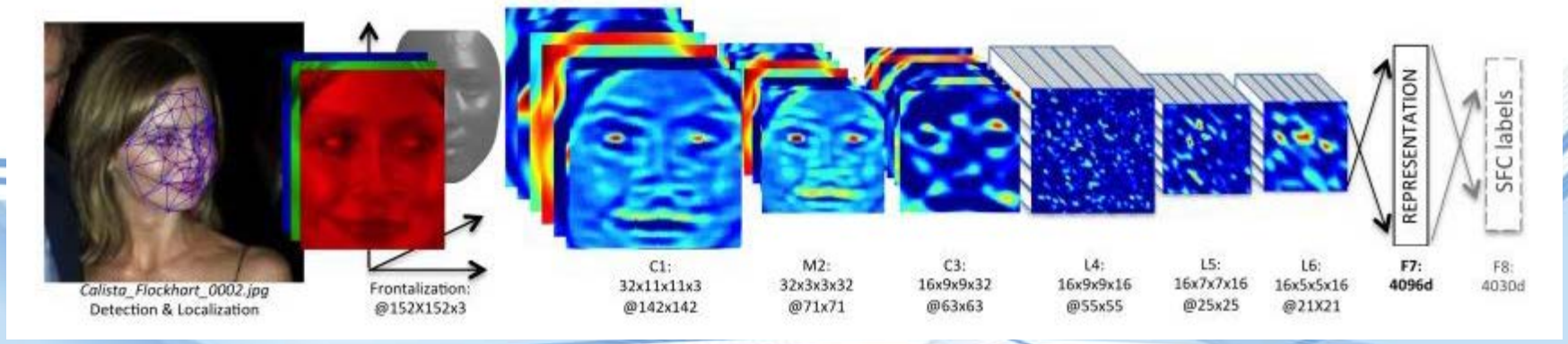
- Arhitectura



http://web.eng.tau.ac.il/deep_learn/wp-content/uploads/2016/11/Face-Recognition-A-Deep-Learning-Approach.pdf

DeepFace -Deep Learning

- Arhitectura- Detalii
  - Straturile 1-3 filtre simple pentru descriptori relvanti
  - Straturile 4-6 se concentreaza pe zonele relevante din imagine
  - Stratul 7 – conectat complet, genereaza un vector 4096 dimensional
    - Reprezentare (sparse) – rara: 75% din valori sunt zero
  - Stratul 8 conectatat complet – 4030 clase - Softmax



http://web.eng.tau.ac.il/deep_learn/wp-content/uploads/2016/11/Face-Recognition-A-Deep-Learning-Approach.pdf

Antrenare si performante

- Antrenata pe SFC cu 4M faces
  - 4030 identities, 800-1200 imagini/persona
- Evaluare pe Labeled Faces in the Wild (LFW)
- Antrenare cu SGD cu momentum de 0.9
- Learning rate 0.01 cu descrestere manuala pana la 0.0001
- Initializare aleatorie
- 15 epoci de antrenare
- 3 zile pe un GPU online

Antrenare si performante

- Acuratete 0.9735±0.0025

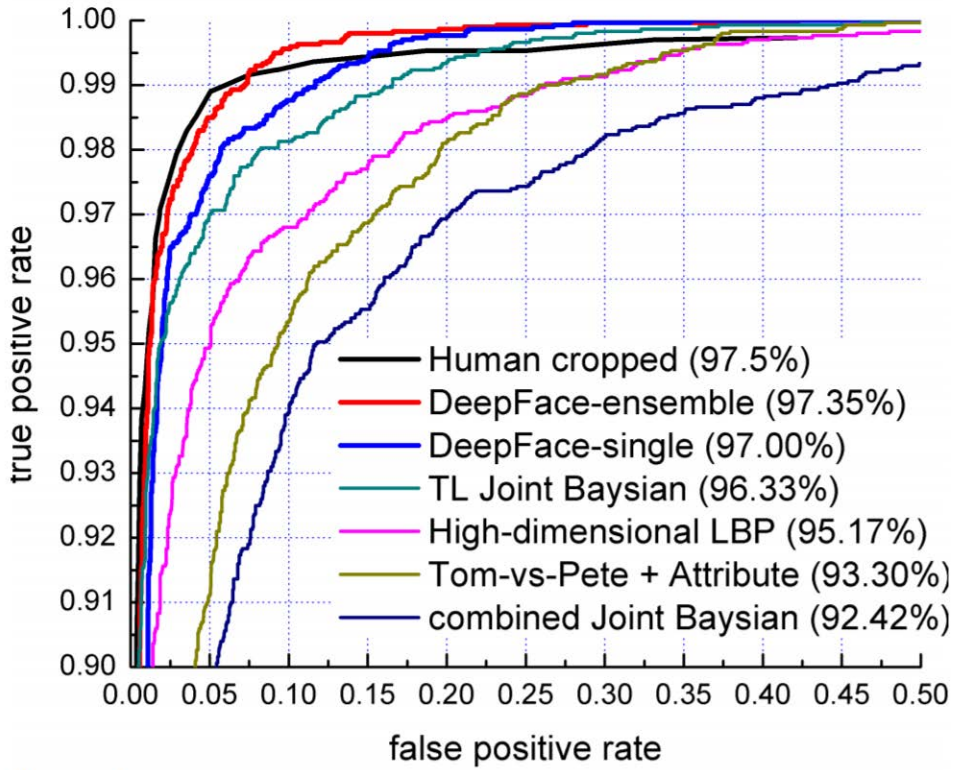
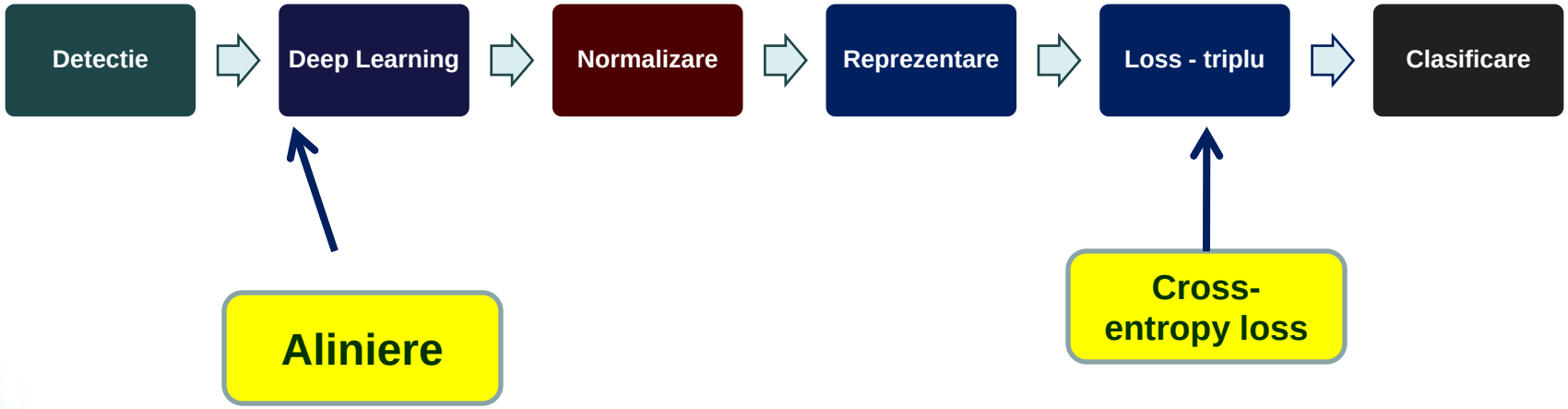


Figure 3. The ROC curves on the *LFW* dataset. Best viewed in color.

FaceNet

- Schroffand Philbin2015



FaceNet

Arhitectura:

- Deep CNN : 22 straturi
- Antreneaza/testeaza pe datele originale
- Stratul final - embedding cu doar 128 dimensiuni/face –> f.f.eficient!
- Imagini triplet pt antrnare si functie obiectiv
- Foloseste SGD, Dropout, ReLU

FaceNet

- Optimizare dupa arhitectura retelei

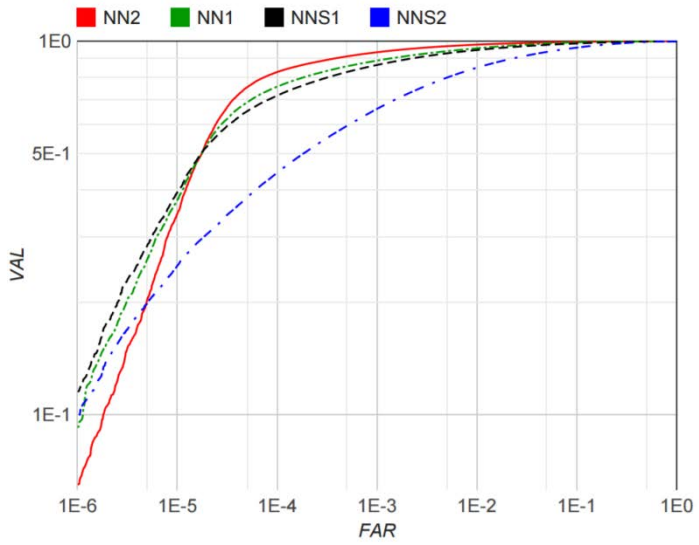


Figure 5. **Network Architectures.** This plot shows the complete ROC for the four different models on our personal photos test set from section 4.2. The sharp drop at 10E-4 FAR can be explained by noise in the groundtruth labels. The models in order of performance are: **NN2:** 224×224 input Inception based model; **NN1:** Zeiler&Fergus based network with 1×1 convolutions; **NNS1:** small Inception style model with only 220M FLOPS; **NNS2:** tiny Inception model with only 20M FLOPS.

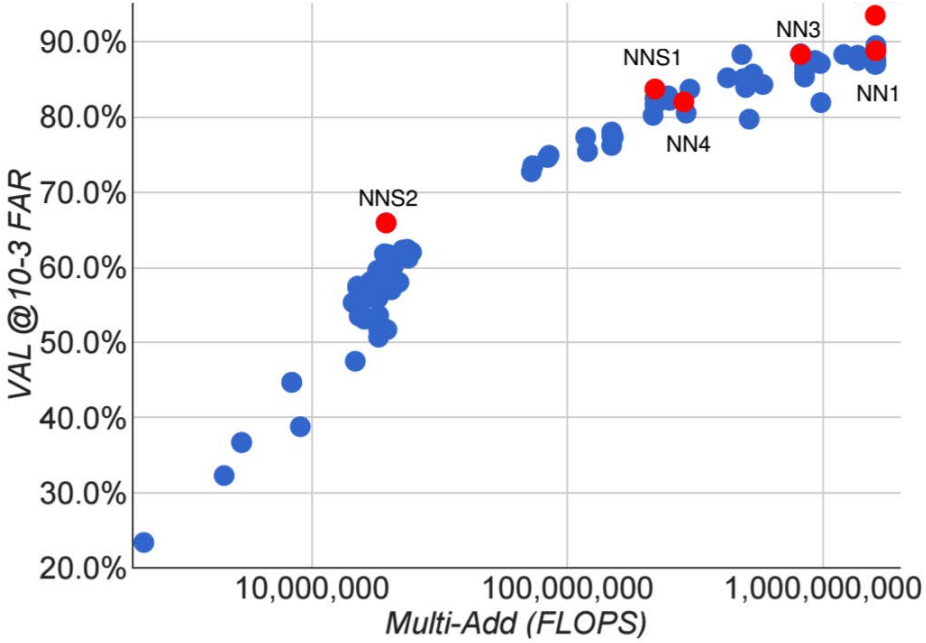


Figure 4. **FLOPS *vs*. Accuracy trade-off.** Shown is the trade-off between FLOPS and accuracy for a wide range of different model sizes and architectures. Highlighted are the four models that we focus on in our experiments.

FaceNet

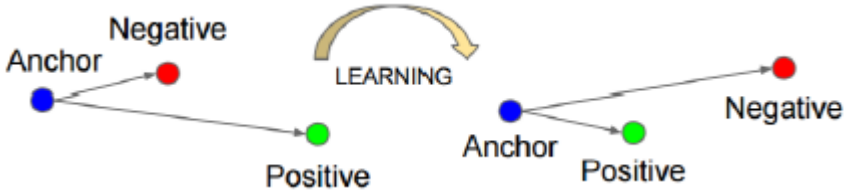
Arhitectura:

- 22 straturi:
  - 11 convolutii
  - 3 normalizari
  - 4 max-pooling
  - 1 concatenation
  - 3 fully-connected
- 140 million parameters

layer	size-in	size-out	kernel	param	FLPS
conv1	220×220×3	110×110×64	7×7×3, 2	9K	115M
pool1	110×110×64	55×55×64	3×3×64, 2	0	
rnorm1	55×55×64	55×55×64		0	
conv2a	55×55×64	55×55×64	1×1×64, 1	4K	13M
conv2	55×55×64	55×55×192	3×3×64, 1	111K	335M
rnorm2	55×55×192	55×55×192		0	
pool2	55×55×192	28×28×192	3×3×192, 2	0	
conv3a	28×28×192	28×28×192	1×1×192, 1	37K	29M
conv3	28×28×192	28×28×384	3×3×192, 1	664K	521M
pool3	28×28×384	14×14×384	3×3×384, 2	0	
conv4a	14×14×384	14×14×384	1×1×384, 1	148K	29M
conv4	14×14×384	14×14×256	3×3×384, 1	885K	173M
conv5a	14×14×256	14×14×256	1×1×256, 1	66K	13M
conv5	14×14×256	14×14×256	3×3×256, 1	590K	116M
conv6a	14×14×256	14×14×256	1×1×256, 1	66K	13M
conv6	14×14×256	14×14×256	3×3×256, 1	590K	116M
pool4	14×14×256	7×7×256	3×3×256, 2	0	
concat	7×7×256	7×7×256		0	
fc1	7×7×256	1×32×128	maxout p=2	103M	103M
fc2	1×32×128	1×32×128	maxout p=2	34M	34M
fc7128	1×32×128	1×1×128		524K	0.5M
L2	1×1×128	1×1×128		0	
total				140M	1.6B

FaceNet

- Antrenare
  - Triplet
  - Model antrenat cu triplete alinaite grosier



$$L = \sum_{i=1}^{N} \left\| f\left(x_i^a\right) - f\left(x_i^p\right) \right\|_2^2 - \left\| f\left(x_i^a\right) - f\left(x_i^n\right) \right\|_2^2 + \alpha \qquad \forall \left(x_i^a, x_i^p, x_i^n\right) \in \mathrm{T}, f\left(x\right) \in \mathbb{R}^d$$

FaceNet- tripletul

- Imperativ pentru convergenta rapida
- Tripletul trebuie sa respecte conditia

$$\left\| f\left(x_i^a\right) - f\left(x_i^p\right) \right\|_2^2 + \alpha < \left\| f\left(x_i^a\right) - f\left(x_i^n\right) \right\|_2^2 \qquad \forall \left(x_i^a, x_i^p, x_i^n\right) \in \mathrm{T}$$

- Selectie online

$$\arg\max_{x_i^p} \left\| f\left(x_i^a\right) - f\left(x_i^p\right) \right\|_2^2, \arg\min_{x_i^n} \left\| f\left(x_i^a\right) - f\left(x_i^n\right) \right\|_2^2$$

FaceNet-Evaluare

- Evaluare pe LFW
  - Acuratete **0.9963±0.09** cu aliniere





Deep Face Recognition

- Parkhi et al BMVC 2015
- Idei principale:
  - Constructia unei baze de date foarte mari cu resurse limitate
    - Introduc o baza de date cu 2.6 Million de fete
  - Recunoasterea fetelor competitiva cu Google si Facebook
    - Rezultate de top pe baza de date Youtube Faces
    - Performanta de top pe LFW

Deep FR – baza de date

1. Cautare pe Web dupa nume de persoane celebre
    1. Cautare pe IMDB, etc.
    2. 5000 identitati
2. Verificare manuala a identitatilor
    1. Selectat imagini relevante
    2. 200 img/ celebritate
    3. Eliminat cazurile slab reprezentate pe Google
    4. Eliminat suprapunerile cu bazele publice

DFR- baza de date

- Ex: Robert Downey Jr - popular



- Ex: Ashley Hamilton – mai putin popular



DFR – baza de data

- Ordonarea exemplelor
  - Se aleg primele 1000 de exemple per identitate dupa o cautare a numelui +”actor” pe Google si Bing
- Rezulta o baza de date cu ~2.6 M fete
- Eliminarea duplicatelor
  - Folosesc VLAD descriptor pentru identificarea dublurilor
- Filtrare manuala
  - Curata setul de date prin verificari manuale.

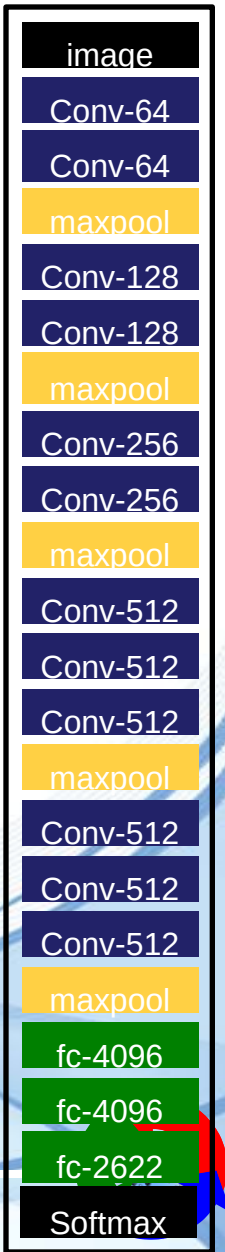
- Procesul a durat 14 zile de munca manuala + timp de rulare in “retrieval”

FaceReg – baze de date

No.	Aim	# Persons	Total # images
1	Labeled Faces In the Wild	5,749	13,233
2	WDRef	2995	99,773
3	Celeb Faces	10177	202,599
4	DeepFace Rec	2622	1,635,159
5	Facebook	4030	4.4M
6	Google	8M	200M

DFR- reteaua

- Arhitectura este “VGG-Face:
  - Nuclee mici 3 x 3
  - Conv. Stride 1 px.
  - Relu non-linearity
  - No local contrast normalisation
  - 3 Fully connected
- Antrenare cu **triplete**
- Antrenare pe 2.6 M faces
  - Solutia foloseste embedding-urile finale



DFR - Rezultate

- LFW

No.	Method	# Training Images	# Networks	Accuracy
1	Fisher Vector Faces	-	-	93.10
2	DeepFace	4 M	3	97.35
3	DeepFace Fusion	500 M	5	98.37
4	DeepID-2,3	Full	200	99.47
5	FaceNet	200 M	1	98.87
6	FaceNet+ Alignment	200 M	1	99.63
7	VGG Face	2.6 M	1	98.95

DFR-rezultate

- YouTube - database

No.	Method	# Training Images	# Networks	100%-EER	Accuracy
1	Video Fisher Vector Faces	-	-	87.7	93.10
2	DeepFace	4 M	1	91.4	91.4
4	DeepID-2,2+,3		200	-	93.2
5	FaceNet + Alignment	200 M	1	-	95.1
7	**VGG Face**	**2.6 M**	**1**	**97.4**	**97.3**

Referinţe bibliografice

Biometrica si problematica generala:

- [Belhumeur] Peter Belhumeur "*Introduction to Biometrics*", Columbia University http://www1.cs.columbia.edu/~belhumeur/courses/biometrics/2010/biometrics.html
- [Sinha] P. Sinha, B. Balas, Y. Ostrovsky, R. Russell, "*Face Recognition by Humans: 19 Results All Computer Vision Researchers Should Know About*", Proceedings of the IEEE, Vol. 94, No. 11, pp. 1948-1962, Noiembrie 2006.

Texture Unit:

- [He] He, D. and Wang, L., "*Texture unit, texture spectrum and texture analysis*," IEEE Trans. on Geoscience and Remote Sensing 28, pp.509-512 Iulie, 1990.

Local Binary Pattern:

- [Ojala1]T. Ojala et al, "*A comparative study of texture measures with classification based on feature distributions*", Pattern Recognition, vol. 29, pp. 51-59, 1996.
- [Ojala2] T. Ojala et al, "*Multiresolution gray-scale and rotation invariant texture classification with local binary patterns*", IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 24, pp. 971-981, 2002.
- [Ahonen] Timo Ahonen et al, "*Face Recognition with Local Binary Patterns*", ECCV 2004, LNCS 3021, pp. 469-481, 2004
- [Pietikäinen] Matti Pietikäinen, "*Face Analysis Using Local Binary Patterns*" http://www.ee.oulu.fi/mvg

Referinţe bibliografice

Recunoastere cu metode 3D:

- [Heseltine] Thomas Heseltine, Nick Pears, Jim Austin *"Three-Dimensional Face Recognition Using Surface Space Combinations "*Advanced Computer Architecture Group, Department of Computer Science - University of York, www.cs.york.ac.uk/~tomh

Deep Learning

- Taigman, Y., Yang, M., Ranzato, M. A., & Wolf, L. (2014). Deepface: Closing the gap to human-level performance in face verification. CVPR Link - https://www.cs.toronto.edu/~ranzato/publications/taigman_cvpr14.pdf
- Schroff, F., Kalenichenko, D., & Philbin, J. (2015). Facenet: A unified embedding for face recognition and clustering, CVPR Link - https://arxiv.org/pdf/1503.03832v3.pdf
- Parkhi, O. M., Vedaldi, A., & Zisserman, A. (2015, September). Deep face recognition. In *BMVC* (Vol. 1, No. 3, p. 6).Link: http://cis.csuohio.edu/~sschung/CIS660/DeepFaceRecognition_parkhi15.pdf