SELECTION AND COMBINATION OF LOCAL GABOR CLASSIFIERS FOR ROBUST FACE VERIFICATION

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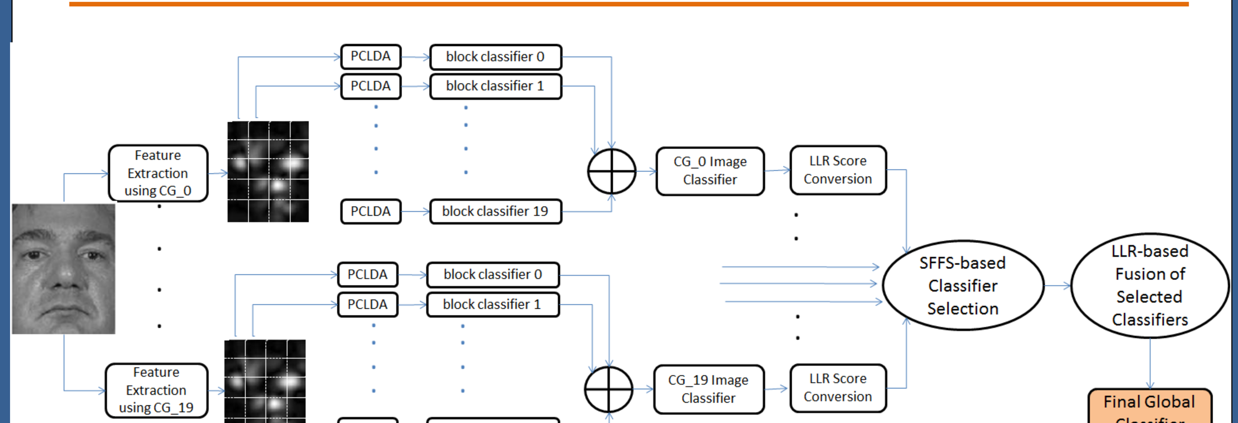
Motivation

- Face recognition under uncontrolled conditions is a popular research area due to its scientific challenges and applications.
  - easily affected by head pose, illumination and facial expression changes, and occlusions and aging.
  - potential applications: video surveillance, smart cards, hci, electronic services such as e-banking and e-home, etc .
- We propose a robust face recognition / verification system which works reliably under uncontrolled conditions.

Our Contribution & Approach

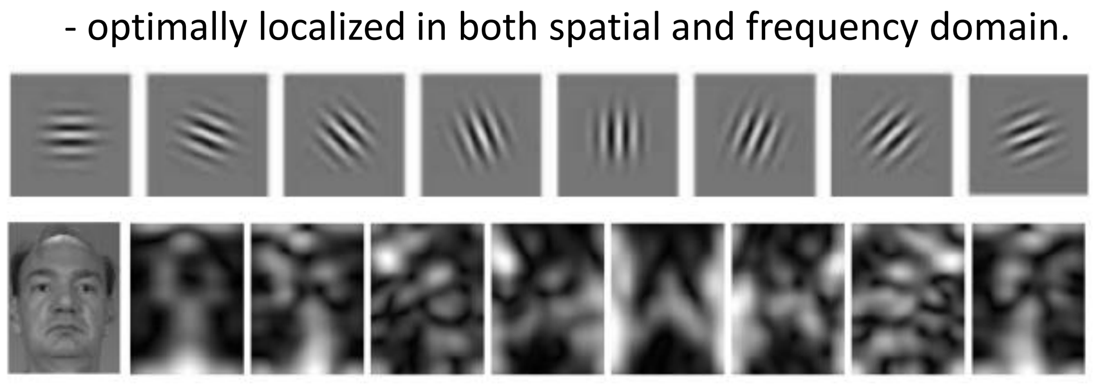
- The main contributions of this work are:
  - comprehensive local curvature Gabor feature extraction,
  - selection and fusion of classifiers,
  - overall system design using modifications on existing methods and smart combination of them,
  - the best reported performance in the literature.

- Our robust face recognition system consists of:
  - face registration,
  - CG feature extraction,
  - generation of CG classifiers,
  - Sequential Forward Floating Search-based classifier selection
  - Log-likelihood ratio (LLR)-based classifier fusion.



Gabor & Curvature Gabor Wavelets

- **Gabor wavelets**:
  - defined as the multiplication of cosine/sine waves with Gaussian kernel window,
  - optimally localized in both spatial and frequency domain.



- **Curvature Gabor wavelets**:
  - a typical face image contains facial components such as eyes, nose, cheeks, lips, and eyebrows. Since these components show curved characteristics rather than straight ones, it is natural to use curvature kernels as well as straight ones.

$$\psi(\mathbf{z};\nu,\mu)=\frac{k_{\nu,\mu}^2}{\sigma^2}e^{(-\frac{k_{\nu,\mu}^2||\mathbf{z}||^2}{2\sigma^2})}[e^{(ik_{\nu,\mu}\mathbf{z})}-e^{(-\frac{\sigma^2}{2})}]$$

Definition of Gabor wavelets

$$\mathbf{z}=\begin{pmatrix}x\\y\end{pmatrix}=\begin{pmatrix}xcos\theta+ysin\theta\\-xsin\theta+ycos\theta\end{pmatrix}$$

The conventional (straight) Gabor formulation

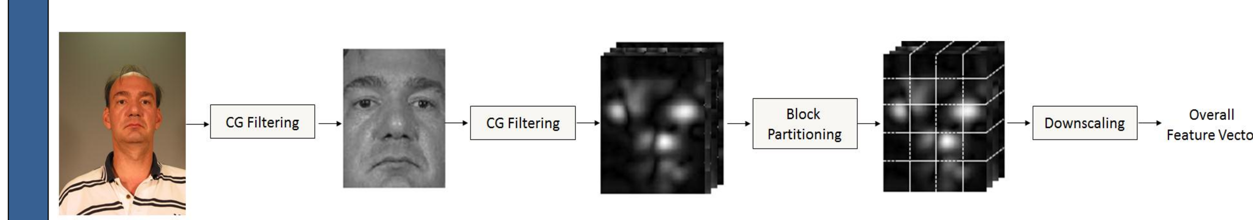
$$\acute{\mathbf{z}}=\begin{pmatrix}\acute{x}\\\acute{y}\end{pmatrix}=\begin{pmatrix}xcos\phi+ysin\phi+c(-xsin\phi+ycos\phi)^2\\-xsin\phi+ycos\phi\end{pmatrix}$$

Curvature Gabor formulation

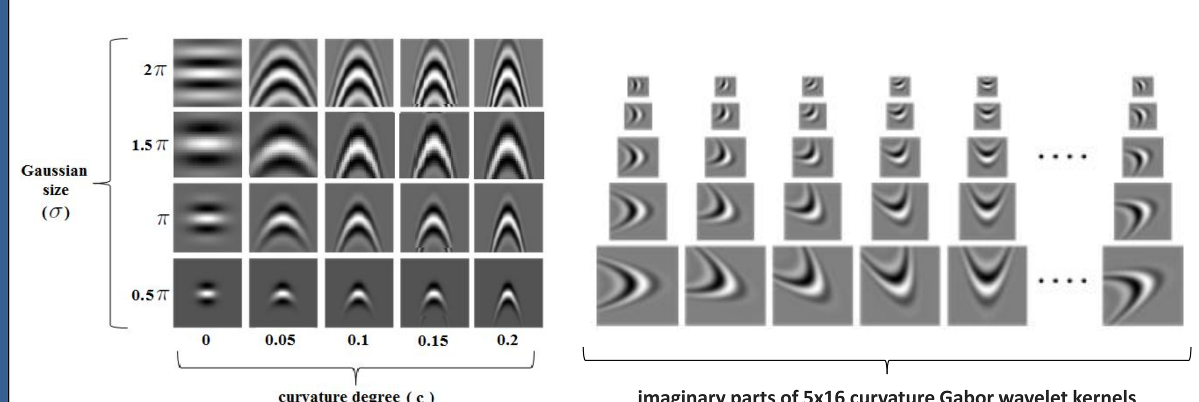
- **Comparison of conventional and curvature Gabor wavelets**:

Properties	Curvature Gabor		Conventional Gabor	
# of Scales	s = 5	; {0,1,2,3,4}	s = 5	; {0,1,2,3,4}
# of Orientations	o = 16	; {0,..,15}	o = 8	; {0,...,7}
Curvature Degrees	c = 5	; {0, 0.05, 0.1, 0.15, 0.2}	c = 1	; {0}
Gaussian Sizes	sigma = 4 ; {2PI, PI, 1.5PI, 0.5PI}		sigma = 1 ; {2PI}	
# of Wavelets	5 x 4 = 20		1 x 1 = 1	
# of Filters	(5 x 16 x 4 x 4) + (5 x 8 x 4)= 1440		5 x 8 x 1 = 40	

Face Registration & Feature Extraction



- **Face registration**:
  - parameters: eye centers and inter-ocular distance
  - information content vs noise trade-off



- **Feature extraction**:
  - high-resolution (HR) images are used, i.e., 128x160 pixels
  - local feature extraction is performed
    1. full convolution of a CG wavelet with the HR face image,
    2. spatial partitioning of each magnitude image into 20 non-overlapping local blocks of size 32x32 pixels,
    3. downscaling the features in each local block by averaging.
  - local feature extraction provides the following advantages:
    1. overcomes the problem of local information loss
    2. makes the system robust to registration errors
    3. provides relatively lower dimensionality

Classifier Generation

- CG block features are Z-normalized before the subspace analysis to centralize the data and normalize the variance.
- We perform PCLDA, that is applying PCA followed by LDA on each block's normalized features independently.
  - this results in 20 local block classifiers based on nearest neighbor with normalized ross correlation as similarity metric
  - the decision of each block classifier is accumulated to form a single image classifier.
- Since there are 5 x 4 = 20 parameter configurations, 20 CG classifiers are generated in overall.

Selection of Classifiers

- Each of 20 CG wavelets is good at representing some particular features; therefore, some classifiers have complementary information when combined with others.
  - we adapt a widely used feature selection algorithm, SFFS, to exploit this complementariness.
- SFFS-based classifier selection algorithm:
  1. Initialization: $Y_0=\{\emptyset\}, VR_{new}=0, k=0$
  2. While $k<20$ and $\Psi(Y_k)\leq VR_{new}$
     - Inclusion of a classifier:
       $\Gamma^+_{LLR}=\underset{\Gamma_{LLR}\notin Y_k}{\text{argmax}}\ \Psi(Y_k+\Gamma_{LLR})$
       If $\Psi(Y_k+\Gamma^+_{LLR})>VR_{new}$
       - Update $Y_{k+1}=Y_k+\Gamma^+_{LLR}$
       - $VR_{new}=\Psi(Y_k+\Gamma^+_{LLR})$
       - $k=k+1$
     - Exclusion of a classifier (backtrack):
       $\Gamma^-_{LLR}=\underset{\Gamma_{LLR}\in Y_k}{\text{argmax}}\ \Psi(Y_k-\Gamma_{LLR})$
       If $\Psi(Y_k-\Gamma^-_{LLR})>VR_{new}$
       - Update $Y_{k-1}=Y_k-\Gamma^-_{LLR}$
       - $VR_{new}=\Psi(Y_k-\Gamma^-_{LLR})$
       - $k=k-1$

References

[1]T. M. Cover and J. A. Thomas. Elements of information theory. New York: Wiley, 1991.
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[3]P. J. Phillips, P. Flynn, T. Scruggs, K. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min, and W. Worek. Overview of the face rec. grand challenge. Proc. IEEE Int. Conf. CVPR, 1:947–954, 2005.

Fusion of Classifiers

- Following from Neyman-Person lemma [1], we perform LLR-based score fusion for combininng selected classifiers to achieve a higher separability between classes.

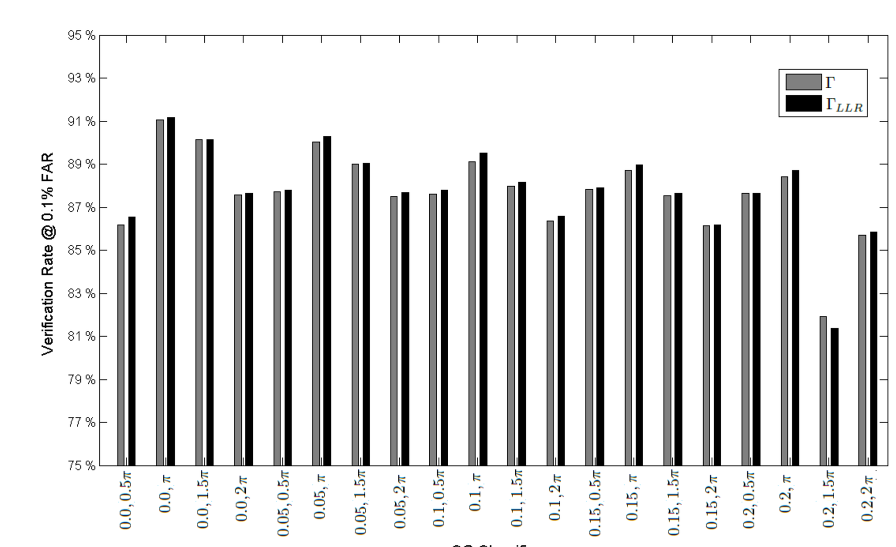
$$\Gamma_{LLR}=log\frac{\mathcal{N}(\Gamma;\mu_{same},\Sigma_{same})}{\mathcal{N}(\Gamma;\mu_{diff},\Sigma_{diff})}$$

  - modeling densities as Gaussian distributions,
  - Gaussian parameters are computed from the training set.

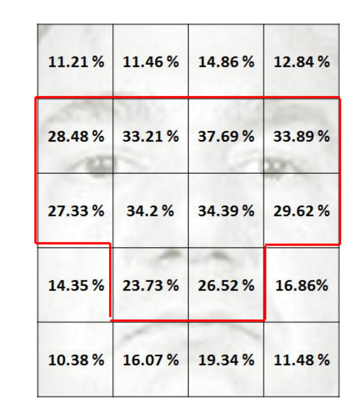
- We also combine global CG classifier obtained above with the local DCT classifier [2] at score level by learning the weights with a statistical technique, PLSR.
  - PLSR is trained on a randomly generated subset of the training set.

Experiments & Results

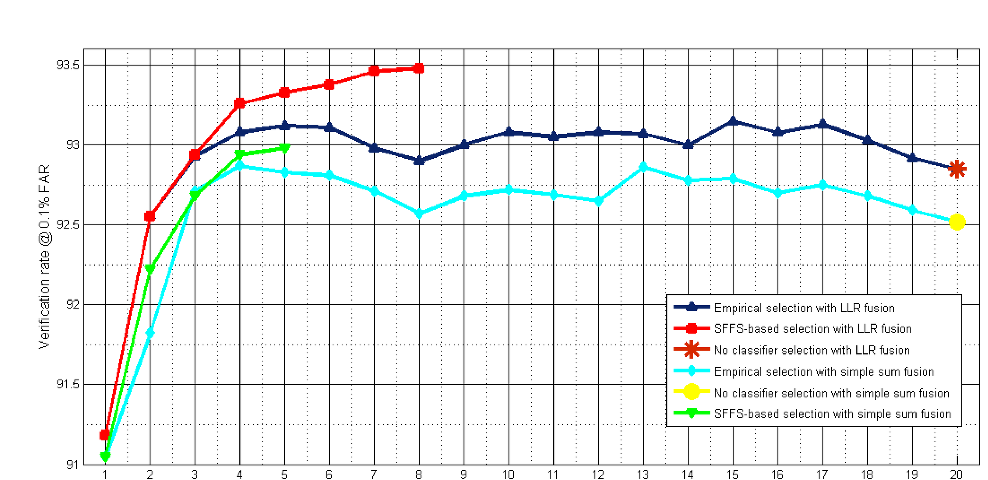
- We evaluated our system on FRGC v2.0 Exp. 4 dataset [3].
- Results on individual CG classifiers:



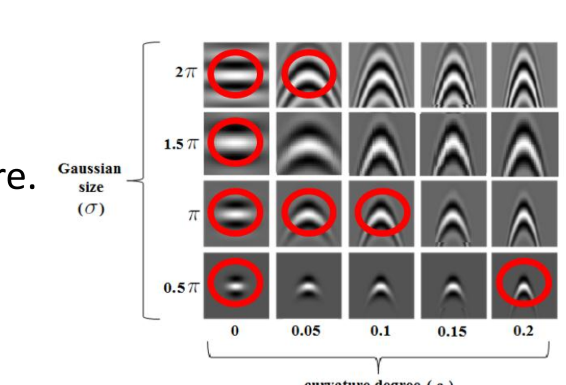
- The best individual classifier achieves 91.05% by a conventional wavelet (0.0, ∏) while the worst one achieves 81.36% by a curvature wavelet (0.2, 1.5∏).
- Results on individual block classifiers of the best individual image classifier:



- Results on fusion of CG classifiers



- Fusion of 8 classifiers achieves **93.46%**, that is better than the best reported result in literature.
- Selected wavelet kernels by SFFS-based classifier selection



- Fusion of final fused CG classifier and the local DCT classifier improves the verification rate to **94.16%.**
- Therefore, we achieved the best verification rate on this dataset reported in the literature.

- Performance comparison with previous work

Method	Features	ROC 3
Hwang, 2006	Holistic Hybrid Fourier	74.33
Kumar, 2006	Holistic Gabor with KFA	76
Tan, 2007	Holistic Gabor + LBP	83.6
Su, 2009	Holistic Fourier + Local Gabor	89
Liu, 2009	Local DCT + LBP + Local Gabor	92.4
Gao, 2010	Multi-res. Local Gabor + Local DCT	92.5
Hwang, 2011	Holistic ECG	90.36
Proposed	Local CG	93.46
Proposed	Local CG + Local DCT	94.16