Robust Face Detection and Recognition Based on Dimensionality-Increasing Techniques

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Overview

- **Face Detection**
  - BDF – Bayesian Discriminating Features Method
  - BDF-SVM in Video using Motion, BDF, SVM

- **Face Recognition**
  - Kernel Methods with Fractional Power Polynomial (FPP) Models
  - Face Recognition Grand Challenge (FRGC) Performance
Bayesian Discriminating Features Method

- DFA – Discriminating Feature Analysis
  - Input Image
  - 1-D Harr Wavelet Representation
  - The Amplitude Projections
- Face and Nonface Class Modeling

\[
\ln\left[p(Y \mid \omega_f)\right] = -\frac{1}{2} \sum_{i=1}^{M} \frac{z_i^2}{\lambda_i} + \frac{\|Y - M_f\|^2}{\rho} - \sum_{i=1}^{M} z_i^2 + \ln\left(\prod_{i=1}^{M} \lambda_i\right) + (N - M)\ln\rho + N\ln(2\pi)
\]
Bayesian Discriminating Features Method

- Bayesian Face Detection

\[ Y \in \begin{cases} \omega_f & \text{if } (\delta_f < \theta) \text{ and } (\delta_f + \tau < \delta_n) \\ \omega_n & \text{otherwise} \end{cases} \]

\[ \delta_f = \sum_{i=1}^{M} \frac{z_i^2}{\lambda_i} + \frac{\|Y - M_f\|^2}{\rho} - \sum_{i=1}^{M} z_i^2 + \ln \left( \prod_{i=1}^{M} \lambda_i \right) + (N - M) \ln \rho \]

\[ \delta_n = \sum_{i=1}^{M} \frac{u_i^2}{\lambda_i^{(n)}} + \frac{\|Y - M_n\|^2}{\varepsilon} - \sum_{i=1}^{M} u_i^2 + \ln \left( \prod_{i=1}^{M} \lambda_i^{(n)} \right) + (N - M) \ln \varepsilon \]

\[ \tau = 2 \ln \frac{P(\omega_n)}{P(\omega_f)} \]
BDF-SVM Face Detection in Video

- BDF-SVM – FaceDT in Video using Motion, Color, DFA
  - SVM – Support Vector Machine

Statistical Learning Theory (SLT) and Structural Risk Minimization (SRM)
BDF-SVM Face Detection in Video

BDF-SVM – FaceDT in Video using Motion, Color, DFA

- SVM – Support Vector Machine
- e.g.: Quadratic Classifier $\rightarrow$ Linear Classifier
- e.g.: Kernel Function: $k(x, y) = (x \cdot y + 1)^d$

$$R^n \rightarrow F : x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \rightarrow \Phi(x) = \begin{pmatrix} x_1 \\ \vdots \\ x_1 \\ x_1^2 \\ \vdots \\ x_1 \cdot x_2 \\ \vdots \\ x_{n-1} \cdot x_n \end{pmatrix}$$

Nonlinear Mapping from Input Space to Feature Space

TSWG: Robust Face Detection and Recognition
BDF-SVM Face Detection in Video

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The Optimal (Maximal Margin) Hyperplane in Feature Space
FPP – Kernel Methods with Fractional Power Polynomial Models

- Kernel Methods

Motivations – Cover’s Theorem on the separability of patterns:
Nonlinearly separable patterns in an input space are linearly separable with high probability if the input space is transformed nonlinearly to a high dimensional feature space.

\[
R^n \rightarrow F : x = \begin{pmatrix}
x_1 \\
x_2 \\
\vdots \\
x_n 
\end{pmatrix} \rightarrow \Phi(x) = \begin{pmatrix}
x_1 \\
x_1^2 \\
\vdots \\
x_n \\
x_1x_2 \\
\vdots \\
x_{n-1}x_n
\end{pmatrix}
\]
Kernel Methods with FPP Models

- FPP – Kernel Methods with FPP Models
  - Kernel Methods
  - Kernel Functions – Mercer Condition

**Kernel Function**

\[ k(x,y) = (\Phi(x) \cdot \Phi(y)) \]

**Gram Matrix**: Given a finite data set \( X = \{X_1, X_2, \ldots, X_M\} \) in the input space and a function \( k : X \times X \rightarrow R(\text{or } C) \), the \( M \times M \) matrix \( K \) with elements \( K_{ij} = k(X_i, X_j) \) is called Gram matrix of \( k \) with respect to \( X_1, X_2, \ldots, X_M \).

**Mercer Condition**: A sufficient and necessary condition for a symmetric function to be a kernel function is that its Gram matrix is positive semi-definite.
Kernel Methods with FPP Models

- FPP – Kernel Methods with FPP Models
  - Kernel Methods
  - Kernel Functions – 3 classes of commonly used
    Polynomial Kernel Functions
      
      $$k(x, y) = (x \cdot y)^d$$

    Gaussian (RBF) Kernel Functions
      
      $$k(x, y) = \exp\left(-\frac{||x - y||^2}{2\sigma^2}\right)$$

    Sigmoid Kernel Functions
      
      $$k(x, y) = \tanh \left( \kappa (x \cdot y)^d + \vartheta \right)$$

    where \( d \in \mathbb{N} \), \( \sigma > 0 \), \( \kappa > 0 \), and \( \vartheta < 0 \)
Experiments – Frontal Faces

- Face recognition performance of the kernel PCA method with three FPP models using the Mahalanobis measure
Kernel Methods with FPP Models

Experiments – Frontal Faces

- Face recognition performance of the Gabor wavelet based kernel PCA method with a fractional power polynomial model using the Mahalanobis measure (99.5% using 246 features for Md_Gabor_0.6)
Kernel Methods with FPP Models

- Experiments – FaceID across Pose
  - Face recognition performance of the Gabor wavelet based kernel PCA method with FPP models using the Mahalanobis measure (95.3% using 64 features for Md_Gabor_0.7)
Face Recognition Grand Challenge (FRGC)

- Face Recognition Grand Challenge (FRGC) Performance
  - 366 FRGC training images
  - 152 FRGC gallery images
  - 608 FRGC probe images