Detecting Faces in Images: A Survey

By: Ming-Hsuan Yang, David J. Kriegman, and Narendra Ahuja

Presented By: Neal Audenaert

Agenda

Introduction

- Approaches
 - Knowledge-based
 - Feature invariant
 - Template matching
 - Appearnce-based
- Databases and Evaluation

Discussion

Agenda

Introduction

- o Approaches
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 - Appearnce-based
- o Databases and Evaluationo Discussion

Introduction

o Domain

- Face detection (not recognition)
- Still images
- Objectives
 - Comprehensive survey of techniques
 - Discussion of performance measures
- Limitations
 - Methods are not directly comparable

Challenges

Pose Structural components • Facial expression Occlusion Image orientation Imaging conditions



General Tasks

- Face localization
- Facial feature detection
- Face recognition
- Face authentication
- Face tracking
- Facial expression recognition

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Survey of Techniques

Knowledge Based

- Top-down
- Bottom-up

Knowledge-based Feature invariant

• Template Based

- Defined templates
- Learned templates

Template matching Appearance-based

Survey of Techniques

Approach	Loc.	Det.
Knowledge-based	Х	
Feature Invariant	Х	
Template Matching	Х	Х
Appearance-based		Х

Knowledge-based Feature Invariant Template Matching Appearance-based

Knowledge-Based Top-Down Methods

Main Idea: Use knowledge about what constitutes a face faces to define rules

Strengths: Frontal faces in uncluttered scenes

Weaknesses:

Translating knowledge into rules Enumeration of cases



Knowledge-Based Top-Down Methods



Bottom-Up Feature-Based Methods

Main Idea: Describe relationships between invariant features using statistical models

Strengths: Improved invariance for different poses and lighting conditions

Weaknesses: Corruption of individual due to illumination, noise, or occlusion

Knowledge-based

Feature Invariant

Template Matching Appearance-based

Bottom-Up Feature-Based Methods

• Facial Features Texture Skin Color Multiple Features

Knowledge-based

Feature Invariant

Template Matching Appearance-based

Template Matching

Knowledge-based Feature Invariant

Main Idea: Find correlation values with a standard face pattern for face contour, eyes, nose, and mouth

Strengths: Simple to implement

Weaknesses: Cannot deal with variation in scale, pose, and shape

Alternatives: Multiresolution, multiscale, subtemplates, and deformable templates

Template Matching

Appearance-Based Methods

Main Idea: Use statistical analysis and machine learning techniques to learn "template" characteristics

Strengths: Most successful approach

Weaknesses: Relatively complex to implement, high-dimensionality requires many training examples

Knowledge-based Feature Invariant Template Matching

Overview of Techniques

Eigenfaces

- Distribution-Based Methods
- Neural Networks (ANN)
- Support Vector Machines (SVM)
- Sparse Network of Winnows (SNoW)

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive • Naïve Bayes Classifier

- Hidden Markov Models (HMM)
- Information Theoretic Approaches

Inductive Learning

Knowledge-based

Feature Invariant

Template Matching

Eigenfaces

• Pedro?

Eigenfaces

Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

- Main Idea: Calculate distance between an instance and exemplary data in a reduced dimensional space
 - Build a face map

Knowledge-based

Feature Invariant

Template Matching

Distribution-Based Methods

 Fit a distribution model to examples

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive Project example into reduced dimensional space

 Build classifier to decide face/non-face

Knowledge-based

Feature Invariant

Template Matching

Sung and Poggio



Baysian HMM Info. Theory Inductive Knowledge-based

Eigenfaces

ANN

SVM SNoW

Distribution

Feature Invariant

Template Matching

Sung and Poggio



Baysian HMM Info. Theory Inductive Knowledge-based

Eigenfaces Distribution

ANN

SVM SNoW

Feature Invariant

Template Matching

Sung and Poggio

Mahalanobis

PCA for each cluster

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

- Representative sample of nonface images?
 - Bootstrap approach

Knowledge-based

Feature Invariant

Template Matching



Yang, Ahuja, Kriegman

• Method 1:

- Factor Analysis
 - Instead of PCA
 - Does not define a mixture model
- Estimate mixture model using EM

o Method 2:

- Fisher's Linear Discriminant
- Class decomposistion using Kohonen's Self Organizing Maps
- ML decision rule to detect faces

Eigenfaces Distribution ANN

SVM SNoW Baysian HMM Info. Theory Inductive

Knowledge-based

Template Matching

Neural Networks

- Two class pattern recognition
- Advantage: capture complex class conditional desnsity
- Drawback: Requires extensively tuning



Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

Eigenfaces

Knowledge-based

Feature Invariant

Template Matching

Support Vector Machines

- Estimating hyperplane is expensive
- Evaluation is fast

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive



Knowledge-based

Feature Invariant

Template Matching

Sparse Network of Winnows

• Detect images with:

- Different features and expressions
- Different poses
- Different lighting conditions

Primitive and multiscale features

- Tailored for domains where
 - Number of features is large
 - Features unknown *a priori*

Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

Knowledge-based

Eigenfaces

Feature Invariant

Template Matching

Naïve Bayes Classifier

- Estimate joint probability of local appearance
 - c.f. bottom-up methods
- Emphasize local appearance
 - Some patterns are more unique
- Detects some ratated and profile faces

Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

Eigenfaces

Knowledge-based

Feature Invariant

Template Matching

Hidden Markov Model



Knowledge-based

ANN

SVM

SNoW

НММ

Baysian

Feature Invariant

Template Matching

Hidden Markov Model

Alternatives

- Karhunen Loeve Traform coefficients as input to HMM
- Use HMM to learn face to non-face transition

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

Knowledge-based

Feature Invariant

Template Matching



Information Theoretic Approaches

Markov Random Fields (MRF)

Model context-dependent entities

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

Kullback relative inforamtion

 Maximize information-based discriminant between the two classes

Knowledge-based

Feature Invariant

Template Matching

Inductive Learning

o C4.5 Algorithm

- Builds a decision tree
- 8x8 pixel window
 - Represented as 30 value vector
 - Entropy, mean, std dev. of pixel value

Find-S

- Gaussian clusters to aproximate distribution of face patterns
- Find-S to learn thresholding

Eigenfaces Distribution ANN SVM SNoW Baysian HMM Info. Theory Inductive

Knowledge-based

Feature Invariant

Template Matching

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AT&T Cambridge Laboratories Face Database



Face Image Databases

Data Set	Location	Description
MIT Database	ftp://whitechapel.media.mit.edu/pub/images/	Faces of 16 people, 27 of each person
[163]		under various illumination conditions,
		scale and head orientation.
FERET Database	http://www.nist.gov/humanid/feret	A large collection of male and female
[115]		faces. Each image contains a single
		person with certain expression.
UMIST Database	http://images.ee.umist.ac.uk/danny/	564 images of 20 subjects.
[56]	database.html	Each subject covers a range of poses
		from profile to frontal views.
University of Bern	ftp://iamftp.unibe.ch/pub/Images/FaceImages/	300 frontal face images of 30 people
Database		(10 images per person) and 150 profile
		face images (5 images per person).
Yale Database [7]	http://cvc.yale.edu	Face images with expressions, glasses
		under different illumination conditions.
AT&T (Olivetti)	http://www.uk.research.att.com	40 subjects, 10 images per subject.
Database [136]		
Harvard Database	ftp://ftp.hrl.harvard.edu/pub/faces/	Cropped, masked face images under
[57]		a wide range of lighting conditions.
M2VTS Database	http://poseidon.csd.auth.gr/M2VTS/index.html	A multimodal database containing
[116]		various image sequences.
Purdue AR	http://rvl1.ecn.purdue.edu/~aleix/aleix_face	3,276 face images with different
Database [96]	_DB.html	facial expressions and occlusions
		under different illuminations.

Features of Databases

- Designed for single study
- o Small
- Highly constrained
- Oriented to face recognition

Benchmark Test Sets



Benchmark Test Sets

Data Set	Location	Description
MIT Test Set [154]	http://www.cs.cmu.edu/~har	Two sets of high and low resolution gray scale
		images with multiple faces in complex background.
CMU Test Set [128]	http://www.cs.cmu.edu/~har	130 gray scale images with a total of
		507 frontal faces.
CMU Profile Face Test	ftp://eyes.ius.cs.cmu.edu/usr20/	208 gray scale images with faces in
Set [141]	ftp/testing_face_images.tar.gz	profile views.
Kodak Data Set [94]	Eastman Kodak Corporation	Faces of multiple size, pose and under varying
		illumination in color images. Designed
		for face detection and recognition.

Performance Evaluation

	Test Set 1		Test Set 2	
Method	Detection Rate	False Detections	Detection Rate	False Detections
Distribution based [154]	N/A	N/A	81.9%	13
Neural network [128]	92.5%	862	90.3%	42
Naive Bayes classifier [140]	93.0%	88	91.2%	12
Kullback relative information [24]	98.0%	12758	N/A	N/A
Support vector machine [107]	N/A	N/A	74.2%	20
Mixture of factor analyzers [175]	92.3%	82	89.4%	3
Fisher linear discriminant [175]	93.6%	74	91.5%	1
SNoW with primitive features [176]	94.2%	84	93.6%	3
SNoW with multi-scale features [176]	94.8%	78	94.1%	3
Inductive learning [38]	90%	N/A	N/A	N/A

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