Object Detection and Recognition in Complex Environmental Conditions

Vijayan K. Asari
University of Dayton
Dayton, Ohio, USA

VISUAL 2016

13 November 2016
Overview

Sensor Data Acquisition -> Sensor Data Exploitation -> Decision and Feedback
Data Acquisition

Distortion correction, enhancement, haze/fog removal, rain removal, stabilization.

Pre-processing

Scene Analysis and Understanding

Wide Area Surveillance

Data Acquisition

Face recognition.
Human action and activity recognition.
Object detection/tracking on WAMI data.
Emotion recognition by EEG analysis.
Brain machine interface.

Decision

Biometric Identification

Human Activity Recognition

Object Detection and Recognition: Processing Pipeline

Face recognition.
Human action and activity recognition.
Object detection/tracking on WAMI data.
Emotion recognition by EEG analysis.
Brain machine interface.

Brain Activity Analysis

Classification

Hardware Acceleration

Spatial domain features

Spectral domain features

Statistical features

Phase features

Classification

Classical and neural network based approaches.
Focus Areas

**Image and Video Preprocessing**
- Enhancement
- Super-resolution
- Haze removal
- Rain removal
- Stabilization

**Wide Area Surveillance**
- Object detection
- Object recognition
- Object tracking
- 3D reconstruction
- Change detection

**Biometrics**
- Face recognition
- Human action and activity recognition
- Expression analysis
- Emotion recognition

**Vision-Guided Robotics**
- Robotic navigation
- Path planning
- Object following
- Behavior analysis
- Threat analysis

**Perception Beyond Visible Spectrum**
- LiDAR data analysis
- Hyperspectral data
- IR/thermal data
- Satellite imagery
- EEG data analysis

**Brain Activity Analysis**
- Emotion recognition
- Brain machine interface
- Source localization
- Neurofeedback
Enhancement of Low Lighting and Over Exposed Images

Underexposed, dark, dark and bright (shadows), bright, overexposed regions
Dynamic Range Compression

Intensity computation (NTSC)

\[ I(x, y) = 0.2989 \times I_{Rh}(x, y) + 0.5867 \times I_{Gh}(x, y) + 0.114 \times I_{Bh}(x, y) \]

Nonlinear function

\[ I_{\text{enh}}(x, y) = (2 / \pi) \text{ArcSin}(I_n(x, y)^{q/2}) \]
Adaptive Estimation of Control Parameter

$q < 1$ Provide various nonlinear curves if the pixels are dark.

$q = 1$ Provides a curve if the pixel has sufficient intensity.

$q > 1$ Provide various nonlinear curves if the pixels are bright.

Depending on the mean value of its neighborhood

$$I_{M_i}(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m,n)G_i(m+x, n+y)$$

$$G_i(x, y) = K \cdot e^{-\frac{(x^2 + y^2)}{w_i^2}}$$

Window size depends on the resolution and object size in an image.
Adaptive Estimation of Control Parameter

Criteria for estimation of $q$

$$q = \begin{cases} < 1, & \text{if } I_{M_n} < 0.5 \\ = 1, & \text{if } I_{M_n} = 0.5 \\ > 1, & \text{if } I_{M_n} > 0.5 \end{cases}$$

The function for the $q$ value can be designed as

$$q = \tan \left( I_{M_n}(x, y) \times (\pi / c_1) \right) + c_2$$

$c_1$ and $c_2$ are empirically determined. $c_1 = 2.25$ $c_2 = 0.0085$

For $q$ values which are closer to 0 the noise in the extreme dark regions will also be enhanced.

Hence, the $q$ values corresponding to the mean value below 0.2 is considered as extreme dark regions and $q$ for those pixels can be calculated as

$$q = \log \left( \sqrt{2I_{M_n}(x, y) + 2} \right);$$
Nonlinear Enhancement Module

Contrast Enhancement

\[ S(x, y) = 255 \times I_{enh}(x, y)^{E(x,y)} \]

\[ E(x, y) = \left[ \begin{array}{c} I_{conv}(x, y) \\ I(x, y) \end{array} \right] \]

Color restoration

\[ I_{enh,i} = I_i(x, y) \left( \frac{I_{enh}(x, y)}{I_n(x, y)} \right) \]

where \( i \) represents red, green, blue spectral band
Enhancement of Low Lighting and Over Exposed Images
Enhancement of Hazy/Foggy Images

Weather Degraded Image: Poor contrast, distorted color

Estimation of approximate thickness of haze in the scene and enhancement using a single nonlinear function.

An adaptive estimation of control parameter from its neighborhood information.
Enhancement of Hazy/Foggy Images
Enhancement of Hazy/Foggy Images
Enhancement of Hazy/Foggy Images

Original Images

Enhanced Images
Scene Visibility Improvement: Rain Removal

With rain

Rain removed
Biometric Data Analysis for Human Identification

- Face Detection
- Action Recognition
- Iris Recognition
- Expression Recognition

- Face Recognition System
- Face Database
- Face Detection System
- Expression Recognition

- Action Recognition System
Human Detection

Input images

Dataset for training the classifier

Sliding window; Stride= 8 pixels

On-line phase

Feature Extraction

Classification

Off-line phase

Class1 (Positive)

Off-line phase

Class2 (Negative)
Framework of the Human Detection System

Chromatic domain phase features with gradient and texture (CPGT)

Input image (RGB)

Compute CSLBP Values (for gray image)

Histogram of CSLBP for local regions (16x16 pixels) (1 histograms)

Gradient magnitude and orientation Computation (for gray image)

HOG of local regions Local region= 16x16 pixels (4x4 cells) Cell= 4x4 pixels. (16 histograms)

PC. / R | PC. / G | PC. / B
Select the maximum phase congruency (one channel).

HOG feature vectors of training datasets

CPGT feature vectors

Linear SVM classifier

Non-maximum suppression

Pedestrian / Non-pedestrian

Fusing local region's histograms

concatenation of the entire image Histograms

CPGT Features

* HOP = Histogram of Oriented Phase  * HOG = Histogram of Oriented Gradient  * CSLBP = Central Symmetric Local Binary Pattern.
CPGT Detector Results
CPGT Detector Results
Face Recognition System

**Face Detection** – quickly and efficiently locates all faces in a given image region.

**Face Features** – calculates unique features of each person in the face database that can be used for accurate classification.

**Feature Classification** – compares features of face regions obtained from the detection process with face feature data computed from the training stage to determine the identity of individuals.
Face Recognition: Appearance Variations

Expression

Pose

Lighting

Occlusion
• Images at various lighting conditions are enhanced to a uniform lighting environment.

• In order to reduce the search space for faces in an image frame, the human skin regions are extracted using the color information.

• Search for faces in all skin regions by using a feature matrix developed by a training process.

• Detected faces are tracked in consecutive frames by statistical analysis performed using the concept of particle filter.

• Manifold learning technique for face recognition.
Skin colors are forming a nonlinear pipe in the RGB space. It is possible to describe the skin color mathematically using the nonlinear manifold.
Face Detection

Training with faces and non-faces.
Dimensionality reduction.
Classification.
Face Detection in Enhanced Images

Original image

Enhanced image

Skin segmented image

Detected faces
Lighting Invariant Face Detection
Pose Invariant Face Detection
Pose Invariant Face Detection
Face Recognition: A Modular Approach

Transform to Subspace (high dimensional vector space to a low dimensional feature space)

Feature Extraction

Face Database

Person #1

Person #2

Probe

Transform to Subspace

Face Identity Classifier

Person #?
Face Recognition: Object Pose and Orientation Variation

Face images are from UMIST face database
Synthetic Database using Single Training Image

Original image

3D Face Model

Generated synthetic 2D images

45 Degree Side-Lighting from both sides

Top-Lighting Overhead

Top-Lighting Overhead with 45 Degree Side-Lighting from both sides

lighting
pose
Face Recognition – Moving Forward!
Object Detection, Tracking, and Identification: Wide Area Motion Imagery Data and IR Data Analysis

Pedestrian tracking

Small boat detection

Whale blow detection in IR video
Wide Area Aerial Imagery Data Analysis

- CLIF – Columbus Large Image Format.
- Data from electro-optic sensors mounted on an aerial platform flying at 7000 feet.
- Six cameras with partially overlapping fields of view.
- Frame size: $4008 \times 2672$ pixels at 2 fps.

Objects of interest – cars, vans, trucks
Moving Object Detection

1. Compute the median image for a group of frames
2. Compute the difference of the frames with the median image
3. Compute the gradient of median image
4. Suppress the gradients in the difference image

Original frame
Difference image
After gradient suppression
Object Tracking

- Feature tracking using **Dense SIFT**
  - Extract SIFT features for every pixel.
  - Dense feature set gives a better representation of the object.
  - Matching is based on the criteria that ratio of distances to first and second closest match should be greater than a particular threshold.
Vehicle Tracking

Tracking multiple objects in a scene with enhancement
Object Tracking with Enhancement and Super-resolution
Pedestrian Tracking

Track pedestrian movement in long range data (CLIF data)

Car
15x15 pixels

Pedestrian
2x7 pixels
Pedestrian Tracking
Classification Problem on CLIF Data

- Low resolution
- Poorly defined contour
- No color information

- Trucks and cars: Intensity distributions are significantly different
  - Enhancement is an important preprocessing step
  - Some fuzziness in the intensity distribution
- Classifiable with Linear SVM
Tracking with Classification
Moving Object Classification

Detecting and classifying moving targets into two classes.
The number of detections significantly improves with super-resolution and enhancement.
Whale Blow Detection in IR Video: Objective

- Detect and track movement of whales during migration
  - Detect presence of whales by detecting whale blows
  - Estimate pod size using timing constraints of whale blows
  - Track whale movement based on their characteristic movement patterns

IR Video: Frame Size: 340 × 280 pixels, Frame Rate: 30 fps
Characteristics of Whale Blows

• Blow appears as a distinct change in the environment.
  • Whale blow is brighter than the background.
  • Distinctive shape when the blow is full-size.

• Two whale blows will not have same base.
  • Presence of significant distance between two whales.

• Temporal characteristics of the blow.
  • Rise period and fall period.
  • Characteristic variation in blow shape.
Whale Blow Detection

Video with whale blow
Whale Blow Detection

With textural variations on the surface
Whale Blow Detection

Multiple whale blows
Oil/Gas Pipeline Right-of-Way Automated Monitoring for Pipeline Encroachment and Machinery Threat Detection

Aerial Imagery

Image Analysis

Object Classification

Threat Localization

Automated System

KML File Mapping

Color Transformation and Enhancement

Key Frame Selection

Key Region Localization

Local Feature Extraction

Object Detection and Identification

Cast Shadows

Low illumination

Partial Occlusion

Small Scale

Orientation
The purpose of developing a part-based model is to cope with partial occlusion and large appearance variations.

Part-based Model for Robust Classification

- Raw Image
- Image Enhancement
- Background Elimination
- Part-based Model for Object Recognition

Tractor
Part-based Model for Robust Classification

- **Object**
- **Partitioning** → **Parts**
- **Feature Extraction and Clustering**
- **Histogram Representation**

Significant Features
Ringlet Part-Based Model

Method: Using Ring Histogram for each part of objects
• Invariant to rotation
• Still contains spatial information
• Still contains partial occlusion ability
Part-based Detection – Non Occlusion

Final Detection Output

- Backhoe

- Most significant parts
- Less significant parts
Part-based Detection – Partial Occlusion

Final Detection Output

Object is occluded by tree

Tractor

Most significant parts
Less significant parts
Brain Signal Analysis: Emotion Recognition and Brain Machine Interface

Independent components

Medical Applications

EEG Data

Brain machine interface

Feature Extraction

Intentions, motives

Classification

Brain Signal Analysis:

EEG Data

Decision

Emotion Recognition and Brain Machine Interface

Control

Efficiency

Stress detection, fatigue assessment
Thanks

Sensing, Processing and Automatic Decision Making in Real Time

www.visionlab.udayton.edu