Unit 8

Applications in Image Processing with Examples

Image Processing

- “Making visible”, e.g. filtering, emphasizing of relevant areas, brightness
- Reconstruction of noisy images
- Compression
- . . .
- High-level interpretation of image content

Applications

- Quality control/assurance
- Robotics
- Process automation
- Security systems (face and fingerprint recognition)
- Traffic surveillance and control
- Content-based image retrieval
- . . .

Challenges

There is an almost infinite number of possible applications where high-level pattern recognition would be helpful in image processing,

BUT

today's methods are still lagging far behind the capabilities of the human eye/brain — in terms of

- robustness and fault tolerance,
- abstraction ability,
- performance (quality and speed),
- etc.

Pattern Recognition

- Feature Selection
- Clustering
- Classification

Fuzzy logic provides a methodology to come a bit closer to the human capabilities of image and scene understanding, in particular, when classification tasks are considered.

Fuzzy Classification Systems

Fuzzy classification systems are ordinary fuzzy systems with usual rule actions:

$$\perp \quad := \quad \langle N_y \rangle \text{ “is” } \langle l_{y_j} \rangle \text{ ;}$$

As usual, $\langle l_{y_j} \rangle$ may be expanded with a corresponding term from T_y. However, the universe X_y and the term set T_y coincide and are finite sets of class labels.

Example

$$T_y = X_y = \{\text{“dog”}, \text{“horse”}, \text{“fish”}\}$$

IF (no-of-legs is four and height is tall)	THEN class is horse
IF (no-of-legs is four and height is short)	THEN class is dog
IF no-of-legs is zero	THEN class is fish

How to Process Fuzzy Classification Rules?

Case 1: Deductive Interpretation

IF *cond*$_i$ THEN N_y is l_{y_i}

Assume that the conditions *cond*$_i$ are fulfilled with degrees t_i. We compute individual output fuzzy sets O_i for each rule in the following way:

$$\mu_{O_i}(x) = \begin{cases} \tilde{I}(t_i, 1) & \text{if } x = l_{y_i} \\ \tilde{I}(t_i, 0) & \text{otherwise} \end{cases}$$

The individual output fuzzy sets are then aggregated by means of the t-norm $\tilde{T}$.

How to Process Fuzzy Classification Rules?

Case 2: Assignment Interpretation

$$\text{IF } \textit{cond}_i \text{ THEN } N_y \text{ is } l_{y_i}$$

Assume that the conditions *cond*$_i$ are fulfilled with degrees t_i. We compute individual output fuzzy sets O_i for each rule in the following way:

$$\mu_{O_i}(x) = \begin{cases} t_i & \text{if } x = l_{y_i} \\ 0 & \text{otherwise} \end{cases}$$

The individual output fuzzy sets are then aggregated by means of the aggregation operator $\tilde{A}$. Most often, the maximum t-conorm $S_{\mathbf{M}}$ is used.

Defuzzification

In many cases, we need a crisp decision to which class the object belongs.

The almost only way to do this defuzzification on a finite universe of class labels is to use that class the membership to which is maximal.

A Case Study from Print Inspection

Motivation:

- The visibility of a defect depends strongly on the structure of the print in the neighborhood
- The first step towards sensitive print inspection is to extract areas from the print which should be treated differently
- Embedding of the segmentation into a print inspection system which applies human-like quality decisions

Goal

Segmentation of an image into the following four types of areas:

Homogeneous area: uniformly colored area;

Edge area: pixels within or close to visually significant edges;

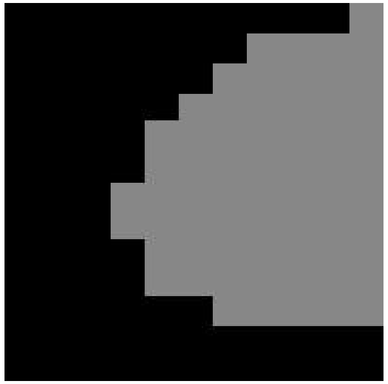
Halftone: area which looks rather homogeneous from a certain distance, but which is actually obtained by printing small raster dots of two or more colors;

Picture: rastered area with high chaotic deviations, in particular small high-contrasted details.

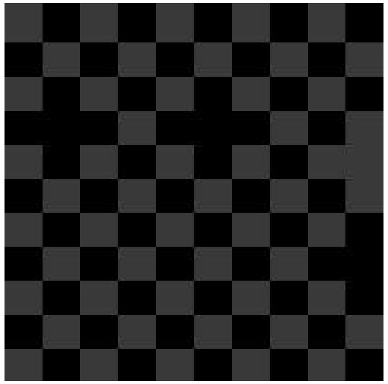
Examples

Homogeneous

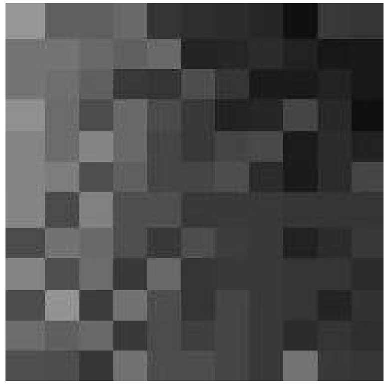
Edge



Halftone



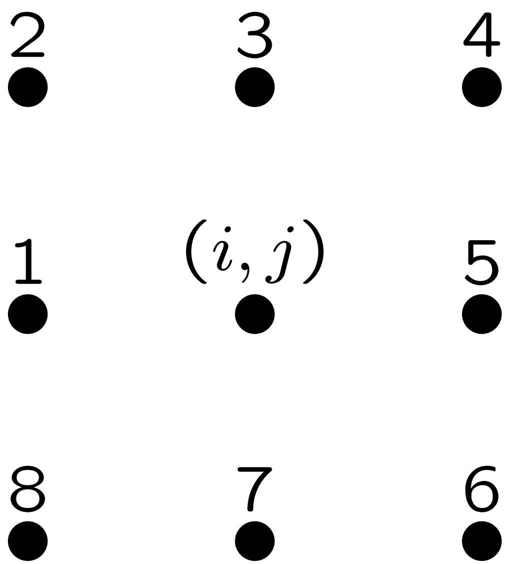
Picture



Solution

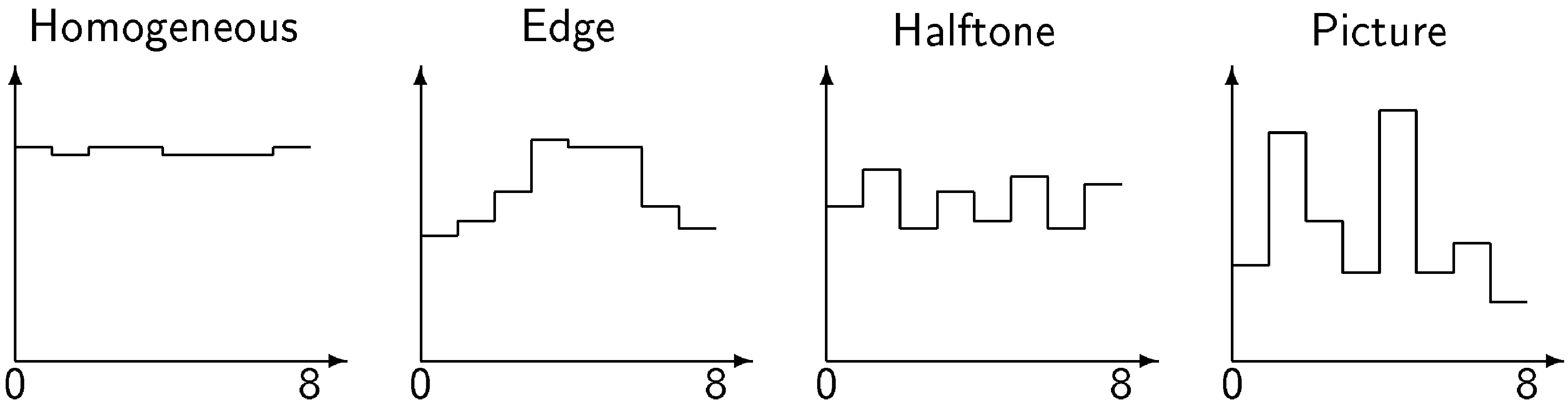
- A fuzzy system with two inputs is evaluated for each pixel independently
- The two inputs are the deviation in the close (3×3) neighborhood and an edge value which is based on the so-called discrepancy norm

Enumeration of the Neighborhood of Pixel (i, j)



k	$l(k)$
1	$(i, j-1)$
2	$(i-1, j-1)$
3	$(i-1, j)$
4	$(i-1, j+1)$
5	$(i, j+1)$
6	$(i+1, j+1)$
7	$(i+1, j)$
8	$(i+1, j-1)$

Gray-Value Curves with Respect to $l(.)$



Some Observations

- Homogeneous areas show low deviations while Halftone areas show medium and Picture areas show high deviations
- The difference between Halftone and Picture areas on the one hand and Edge areas on the other hand is that Edge areas show a small number of connected peaks while Picture and Halftone show chaotic peaks.

The Two Inputs

$$v(i,j) \quad := \quad \sum_{k=1}^{8} (u_r(l(k)) - \overline{r})^2 + \sum_{k=1}^{8} \left(u_g(l(k)) - \overline{g}\right)^2 + \sum_{k=1}^{8} \left(u_b(l(k)) - \overline{b}\right)^2$$

$$e(i,j) \quad := \quad \|u_r(l(.)) - (\overline{r}, \ldots, \overline{r})\|_D + \|u_g(l(.)) - (\overline{g}, \ldots, \overline{g})\|_D + \|u_b(l(.)) - (\overline{b}, \ldots, \overline{b})\|_D$$

where $\overline{r} := \frac{1}{8} \sum_{k=1}^{8} u_r(l(k)),\ \overline{g} := \frac{1}{8} \sum_{k=1}^{8} u_g(l(k)),\ \overline{b} := \frac{1}{8} \sum_{k=1}^{8} u_b(l(k))$

The Discrepancy Norm

$$\begin{aligned} \|.\|_D : \quad \mathbb{R}^n & \longrightarrow \mathbb{R}^+ \\ \mathbf{x} & \longmapsto \max_{1 \leq \alpha \leq \beta \leq n} \left| \sum_{i=\alpha}^{\beta} x_i \right| \end{aligned}$$

Remarks

- The discrepancy norm $\|.\|_D$ can be computed in linear time, since

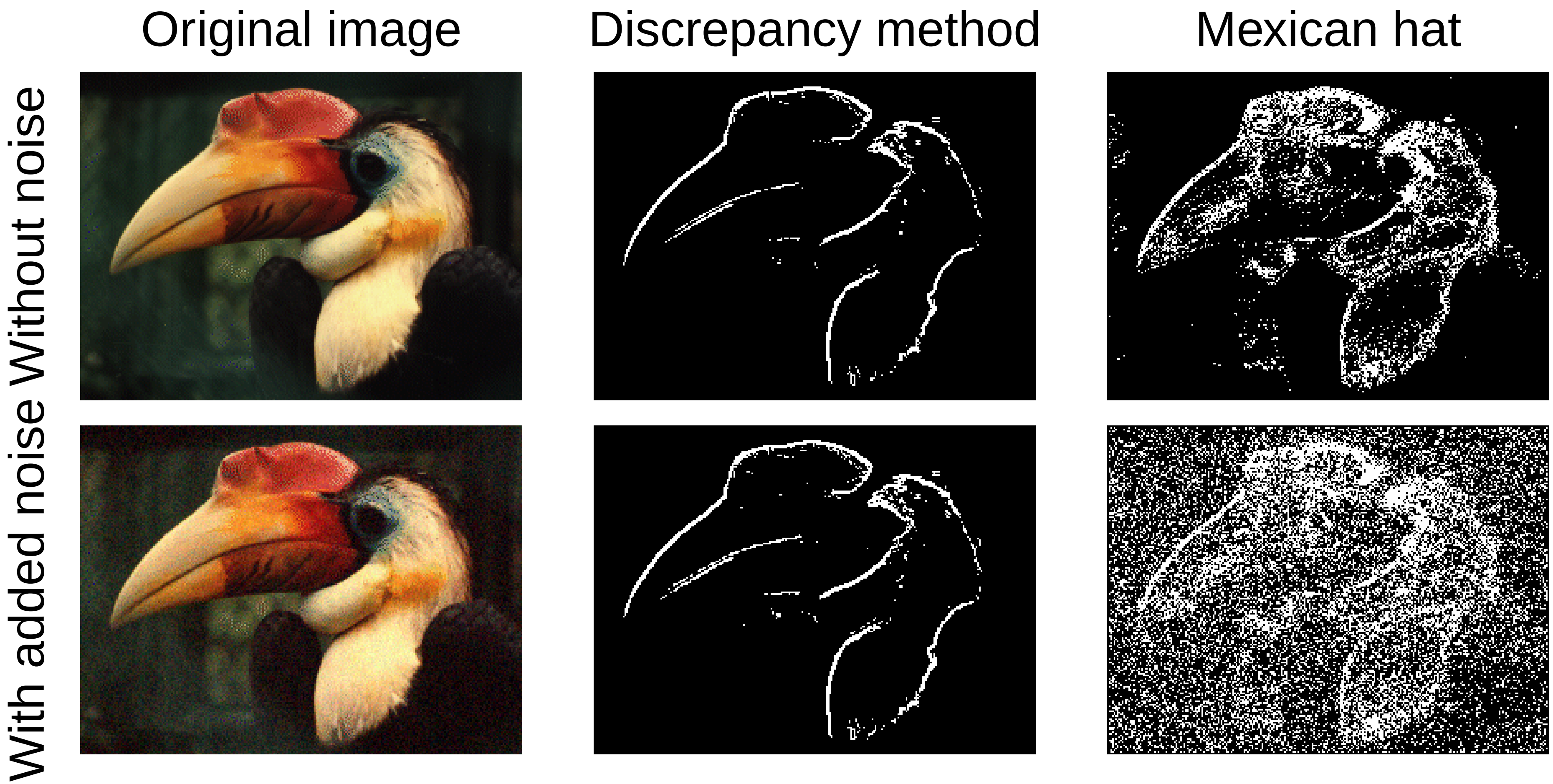
$$\|\mathbf{x}\|_D = \max_{1\leq\beta\leq n} X_\beta - \min_{1\leq\alpha\leq n} X_\alpha,$$

where

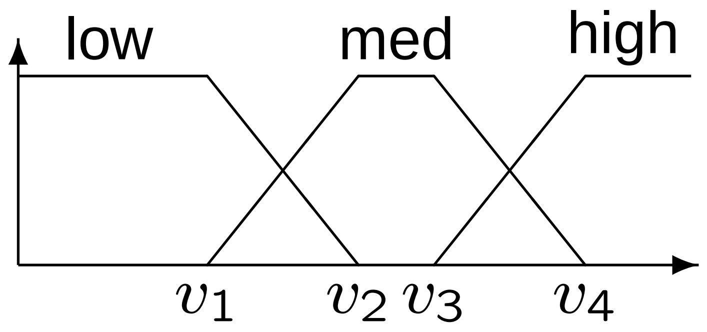
$$X_k = \sum_{i=1}^{k} x_i.$$

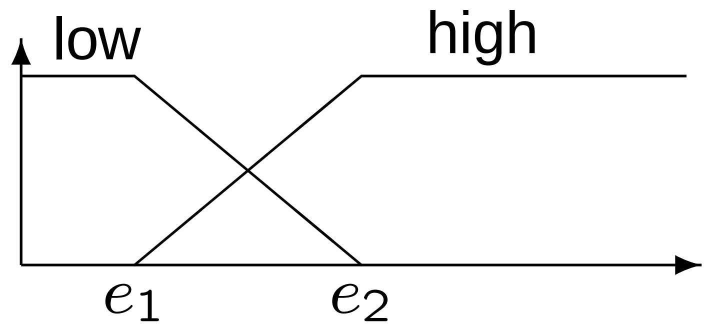
- The discrepancy approximately measures the area under the largest peak. So, it can be used to distinguish between Halftone and Picture on the one hand and Edge on the other hand.

The Discrepancy Measure $e(i, j)$ as an Edge Detector



The Fuzzy System

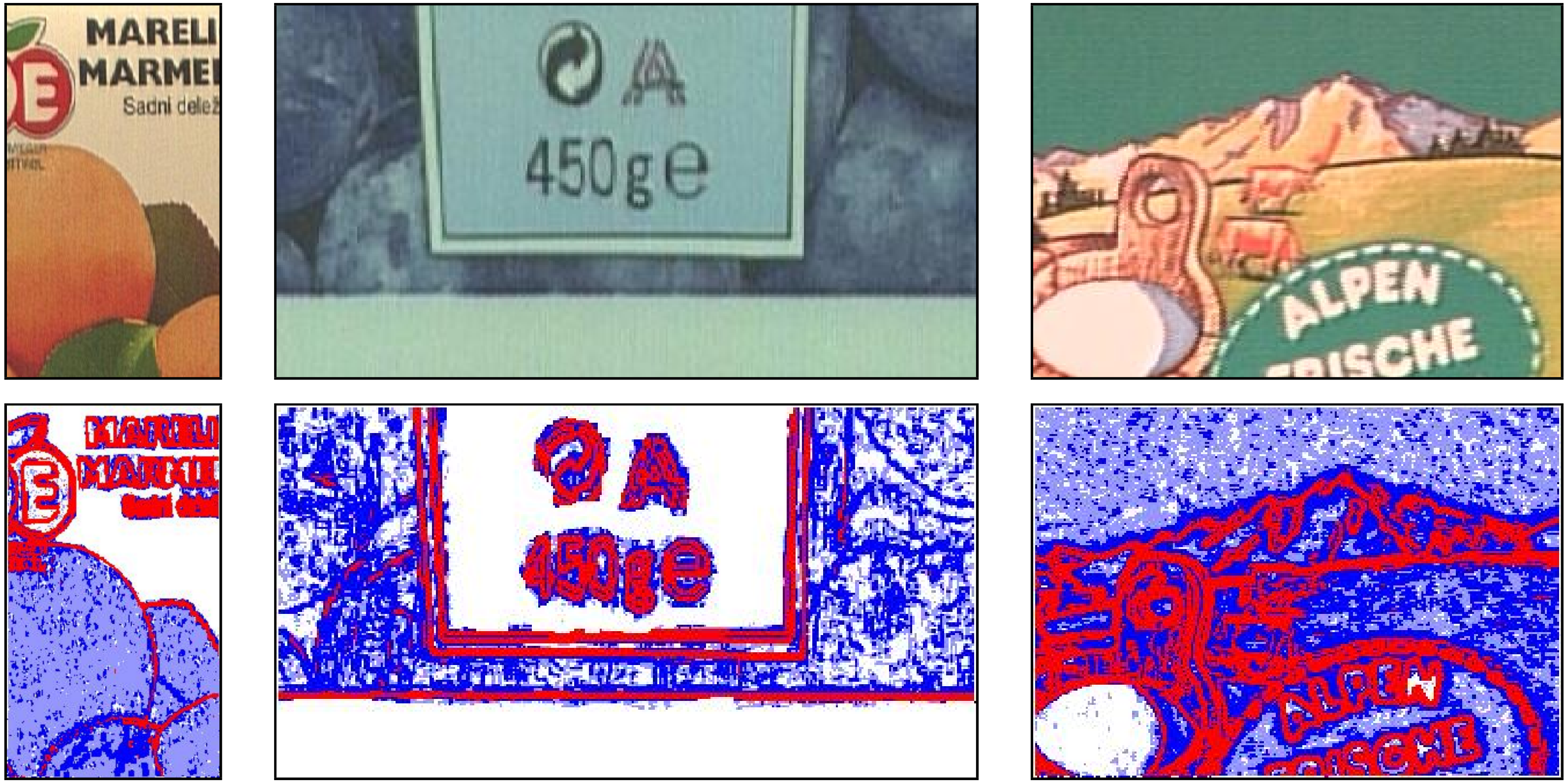




IF	v is low			THEN	t is Ho
IF	v is med	AND	e is high	THEN	t is Ed
IF	v is high	AND	e is high	THEN	t is Ed
IF	v is med	AND	e is low	THEN	t is Ha
IF	v is high	AND	e is low	THEN	t is Pi

This rulebase is evaluated for each pixel independently using the Mamdani max-min inference.

Some Results



□ . . . Homogeneous ■ . . . Edge ■ . . . Halftone ■ . . . Picture

Summary

This classification problem has been solved in the following way:

Feature selection: computation of parameters $v(i, j)$ and $e(i, j)$

Classification: by means of a simple fuzzy rule base whose inputs are $v(i, j)$ and $e(i, j)$ and whose output is the final classification of the pixel (i, j)

Commercial Applications in Consumer Goods

- Jiggle-free video cameras
- Autofocus systems
- Auto-exposure systems
- . . .

Large-Scale Commercial Applications

- Print inspection
- Intelligent robots with vision capabilities
- . . .