Key Concepts of Pattern Recognition An Introduction to Pattern Recognition



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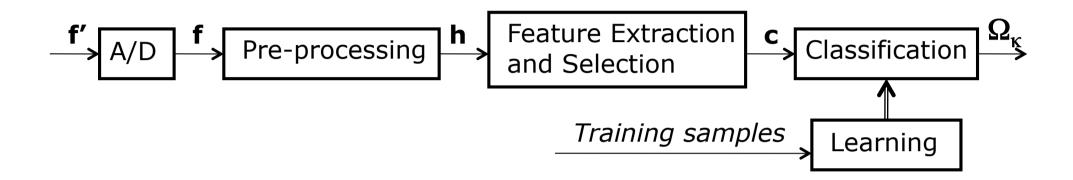
What is Pattern Recognition?



- Definition: Pattern Recognition involves the design of systems that (semi) automatically recognize patterns in sensed data.
- It deals with the mathematical and technical aspects of determining facts from sensor data.
- Thus, the task of Pattern Recognition needs the following components:
 - Sensor
 - Preprocessing Modules
 - Features
 - Classifier

Pattern Recognition Pipeline

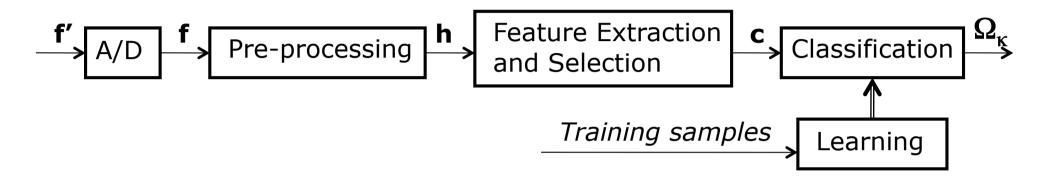




- In recognizing a particular pattern, the entire pattern is treated as a single unit. It is assigned as a whole to a particular class Ω_{κ} out of k possible classes Ω_{λ} , $\lambda = 1,...,k$, without consideration to other patterns.
- It is also possible to reject a pattern, i.e. to assign it to a rejection class Ω_0 .

Properties of the PR Pipeline





- Output of module i is input to module i + 1.
- Simple system structure.
- Each module can be optimized separately (at least partially).
- The sequence of processing steps is relatively independent of the individual pattern.
- Errors in module i will be propagated to i + 1.

Example: Coffee Bean Classification



Sensor:

Color camera

Features:

- Color (light, medium, dark)
- Uniformity of color
- Size
- Smoothness
- Position of the crack (center, or off-center)
- Curvature of the crack (wrinkly, straight, curved)

Classes:

- Grade 1 (specialty grade)
- Grade 2 (premium grade)
- Grade 3 (exchange grade)
- Grade 4 (standard grade)
- Grade 5 (off grade)



Example: Coffee Bean Classification



Sensor:

Color camera

Features:

- Color (light, medium, dark)
- Uniformity of color
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- Position of the crack (center, or off-center)
- Curvature of the crack (wrinkly, straight, curved)
- Weight

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Example: Coffee Bean Classification



Sensor:

- Color camera
- Scale

Features:

- Color (light, medium, dark)
- Uniformity of color
- Size
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- Position of the crack (center, or off-center)
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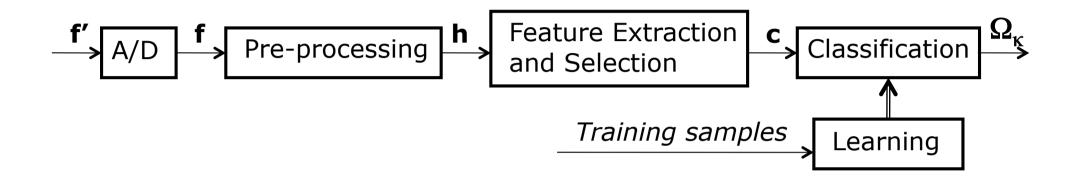
Classes:

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PR Pipeline Reminder





In recognizing a particular pattern, the entire pattern is treated as a single unit. It is assigned as a whole to a particular class Ω_{κ} out of k possible classes Ω_{λ} , $\lambda = 1,...,k$, without consideration to other patterns.

1	5	6	7	а	f	h	q	G	O	Q	S
1	5	6	7	a	f	h	q	G	O	Q	S
1	5	6	7	а	f	h	q	G	0	Q	S
1	5	6	7	a	f	h	q	G	0	Q	S
1	5	6	7	а	f	h	q	G	O	Q	S
1	5	6	7	a	f	h	q	G	О	Q	S
1	5	6	7	a	f	h	q	G	0	Q	S
1	5	6	7	a	f	h	q	G	0	Q	S
1	5	6	7	a	f	h	q	G	0	Q	S
1	5	6	7	a	f	h	q	G	O	Q	S
$\boxed{\hspace{0.1cm}}$	\downarrow										
Ω1	Ω2	Ω3	Ω4	Ω5	Ω6	Ω7	Ω8	Ω9	Ω10	Ω11	Ω12

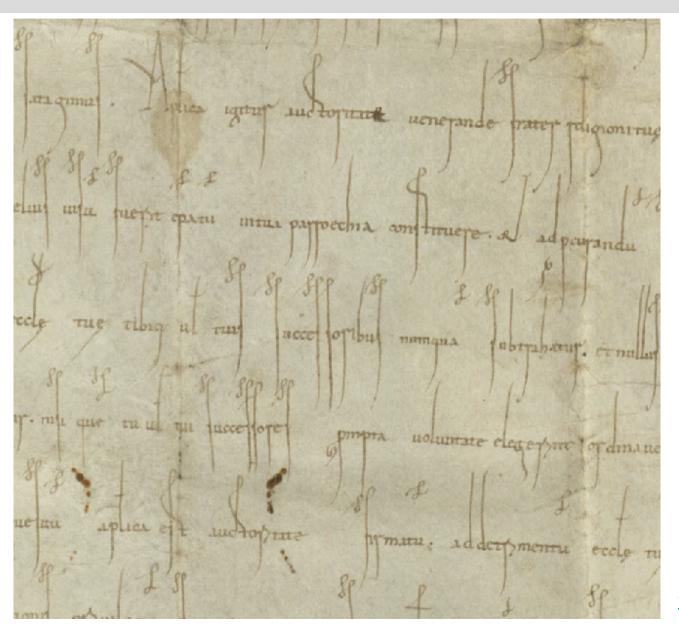


PR on Handwritten Digit Recognition



Our Current Handwriting Recognition Task



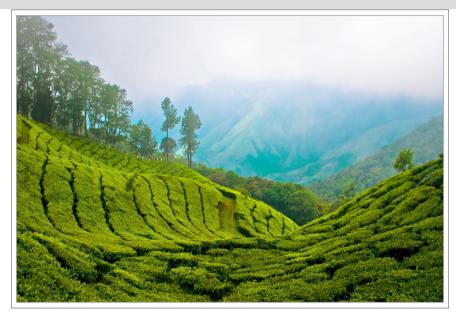


Snippet courtesy of the Monasterium archives, www.monasterium.net

PR on Tea Plants











PR on Speech





- The shown speech signal contains the word chain:
 Ich will morgen abend nach Frankfurt
- The recognition of each word and the recognition of the meaning of the entire sentence is part of an automated system for booking train tickets.

On Recognition



- The task of recognition (speech, faces, diseases, animals, etc.) is a difficult task that humans perform exceptionally well.
- According to Z. Pawlak (1991): Knowledge is deepseated in the classificatory abilities of human beings and other species.
- Also according to Z. Pawlak (1991): Classification on more abstract levels seems to be a key issue in reasoning, learning, and decision making ...

The Postulates of Pattern Recognition



- Understanding a pattern by a machine is equivalent to a mapping from the pattern to an internal schema for knowledge representation
- For Pattern Recognition to work we rely on six key postulates:

1. Sample:

We have representative samples for each class $f(x) \in \Omega$

There is no better data than more data!



2. Features:

Intuitively a feature is a property that we can use to recognize or differentiate units.

Features for finding a face:



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Features for finding a face:

- eyes
- nose
- mouth



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Features for identifying a particular face:



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Intuitively a feature is a property that we can use to recognize or differentiate units.

Features for finding a face:

- eyes
- nose
- mouth

Features for identifying a particular face:

- shape, size, position and color of eyes
- shape, size and position of nose
- shape, size and position of mouth
- hair color
- scars



2. Features:

A simple pattern has features c_v , v = 1,...,n, that are characteristic for the class the pattern belongs to.

A classifier is as good as its features.

If the features can't describe (don't capture) the difference between O and Q (if we miss the little line at the bottom), then we can't expect the classifier to recognize these two letters as belonging to different classes.

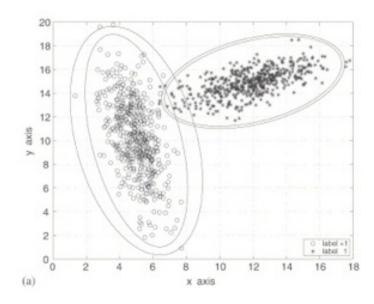
Keep the number of dimensions *n* low (curse of dimensionality).

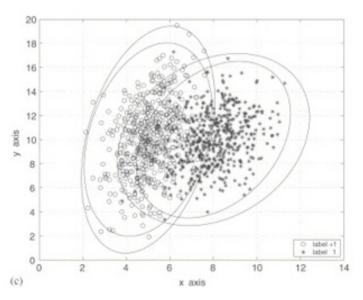


3. Compactness:

Features of patterns belonging to class Ω_{κ} occupy a compact area in feature space.

For a better differentiation between classes we want low intra-class distance and high inter-class distance





Plots courtesy of I. Buciu, C. Kotropoulos and I.Pitas "Demonstrating the Stability of support Vector Machines for Classification."



4. Decomposition:

A complex pattern can be decomposed into smaller parts whose combined presence makes up the pattern.

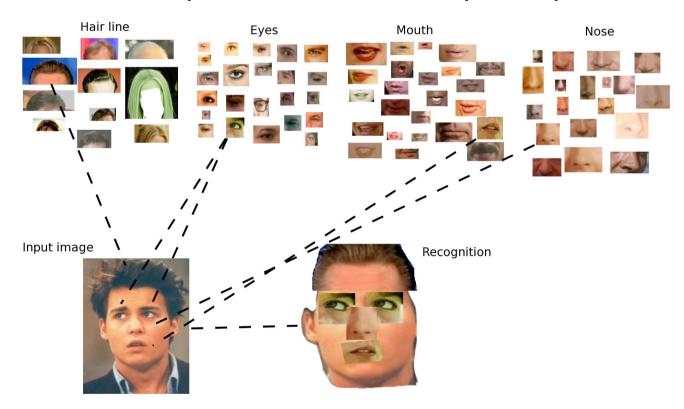
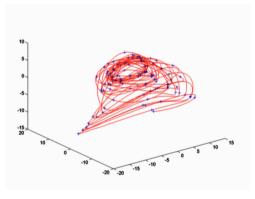


Image courtesy of videosurf, http://www.videosurf.com/blog/the-magic-behind-videosurfs-computer-vision-video-search-engine-56/

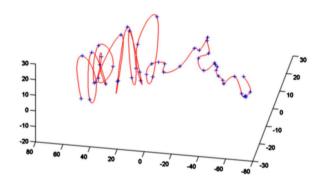


5. Structure:

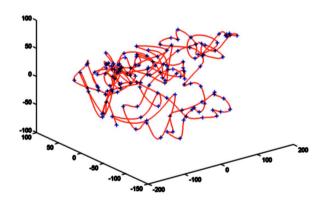
Complex patterns of a specific domain have a certain structure.



Representation of a bird flying. The periodic action of the wings can be clearly seen. As the bird moves towards the camera, its size changes causing a helical structure.



Representation of a bird flying and then gliding. The motion is periodic in the beginning, but the periodicity later stops. This can be seen in the structure of the feature space.



Representation of a water falling in a fountain. The irregularity of the structure in the feature space reflects the lack of regular motion.



6. Similarity:

Two representations (of patterns) are similar if a properly chosen distance measure is small.

- Pattern recognition is based mostly on postulates: 1, 2, 3, 6
- Computer vision is based mostly on postulates: 1, 4, 5, 6

Pattern Recognition Pipeline





Simple Example



Very often in Pattern Recognition we have a training set:

$$T = \{ (\vec{f}_1, \Omega_{\kappa 1}), (\vec{f}_2, \Omega_{\kappa 2}), \dots, (\vec{f}_m, \Omega_{\kappa m}) \}$$

- From such a training set we learn how features (signals) that belong to a particular class Ω_{κ} should look like.
- Given a new feature-vector (signal) we decide that it belongs to the class, which based on our training data, has features (signals) that look the most similar to the new data.

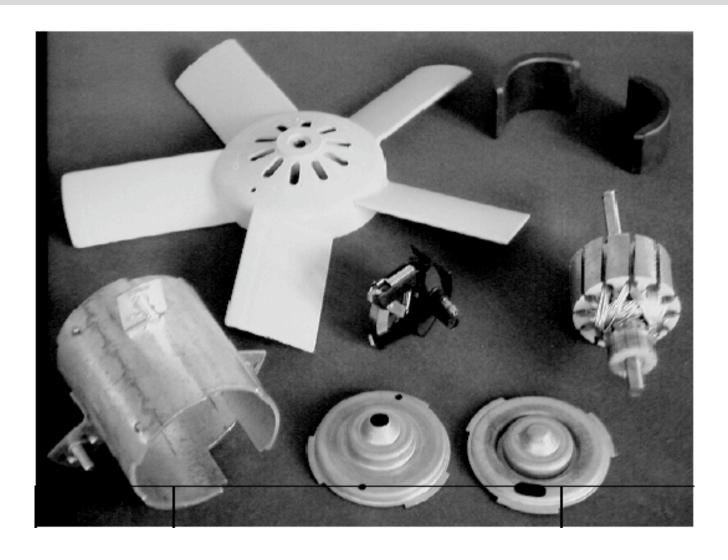
Data Collection



- The first step in a PR system is sensing the environment.
- Data, which is typically in analog form, has to be converted to a digital form so that it can be in a form amenable for further processing.
- There is a very wide variety of what can be used as input in a PR system. It typically depends on the application.
- Selecting the sensor that gives the best quality data at a reasonable cost and speed can be critical in the success of a PR system.

Images: Grayscale 2D data





Images: Color Data over Time - 3D Data











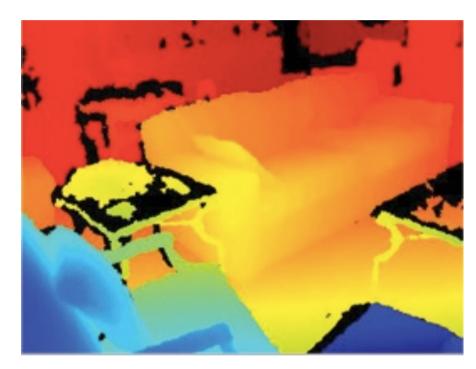




Multiple Sensors: Color and Depth



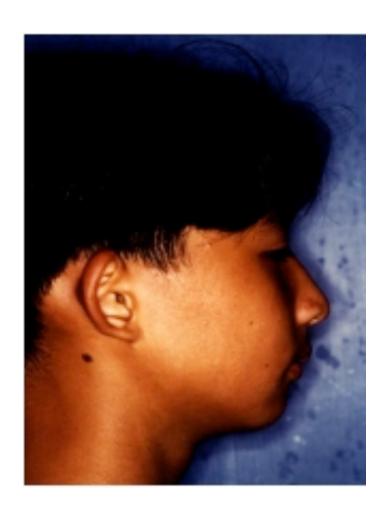




Images from Kinect Sensor courtesy of N. Silberman, P. Kohli, D. Hoiem and R. Fergus from the NUY Depth Dataset V2, http://cs.nyu.edu/~silberman/datasets/nyu depth v2.html

Multiple Images: Color plus X-Ray

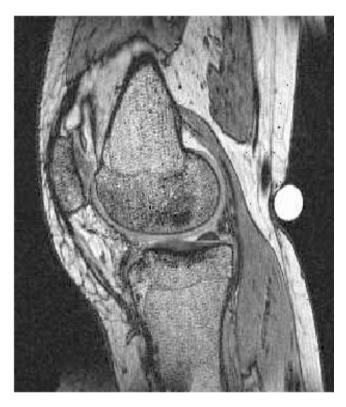


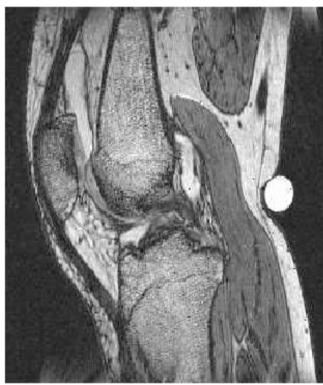


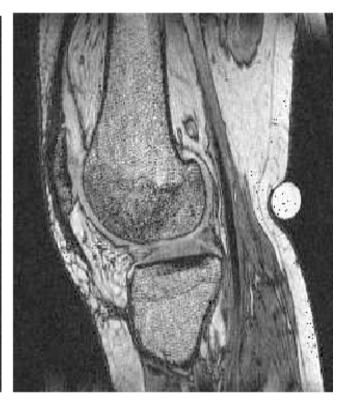


Magnetic Resonance Images: Multiple Slices





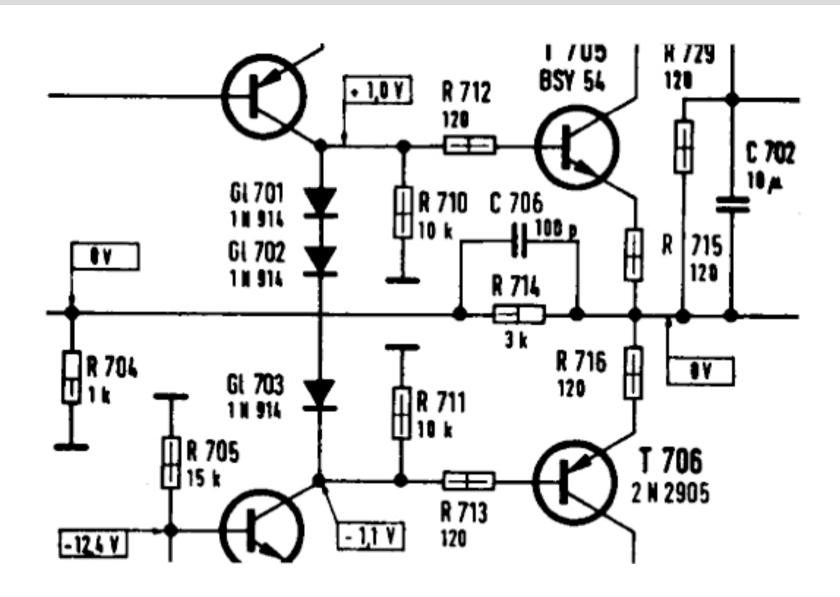




Knee slice 16 Knee slice 22 Knee slice 34

Schema Images





Seismic Data



