

Ontology Based Object Learning and Recognition

PhD Defense

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Talk Overview

- ➔ • Introduction
- State of the Art
- Phase 1: Knowledge Acquisition
- Phase 2: Visual Concept Learning
- Phase 3: Object Categorization
- Results
- Conclusion

Introduction

- ***Problem:*** Semantic Image Interpretation
 - Object Categorization
- Cognitive vision approach *[Auer et al. 04]*
- Abilities of cognitive vision systems:
 - knowing
 - understanding
 - reasoning
 - learning

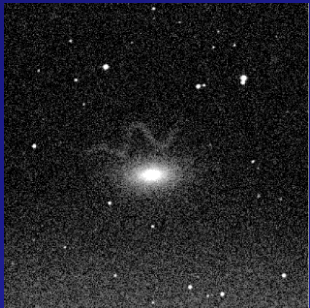
Introduction: Semantic Image Interpretation



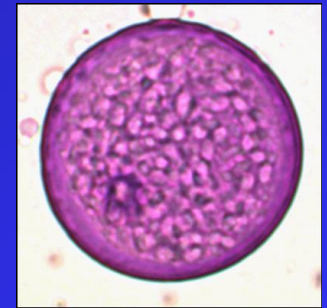
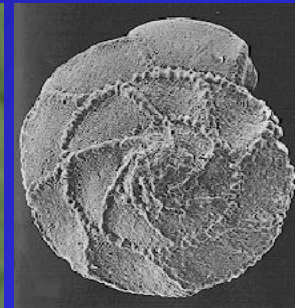
Oslo Accords (1993)

- ➡ By using a priori knowledge in international politics, this image has a completely different meaning
- ➡ Semantics is not inside the image

Introduction: object categorization



Aircraft



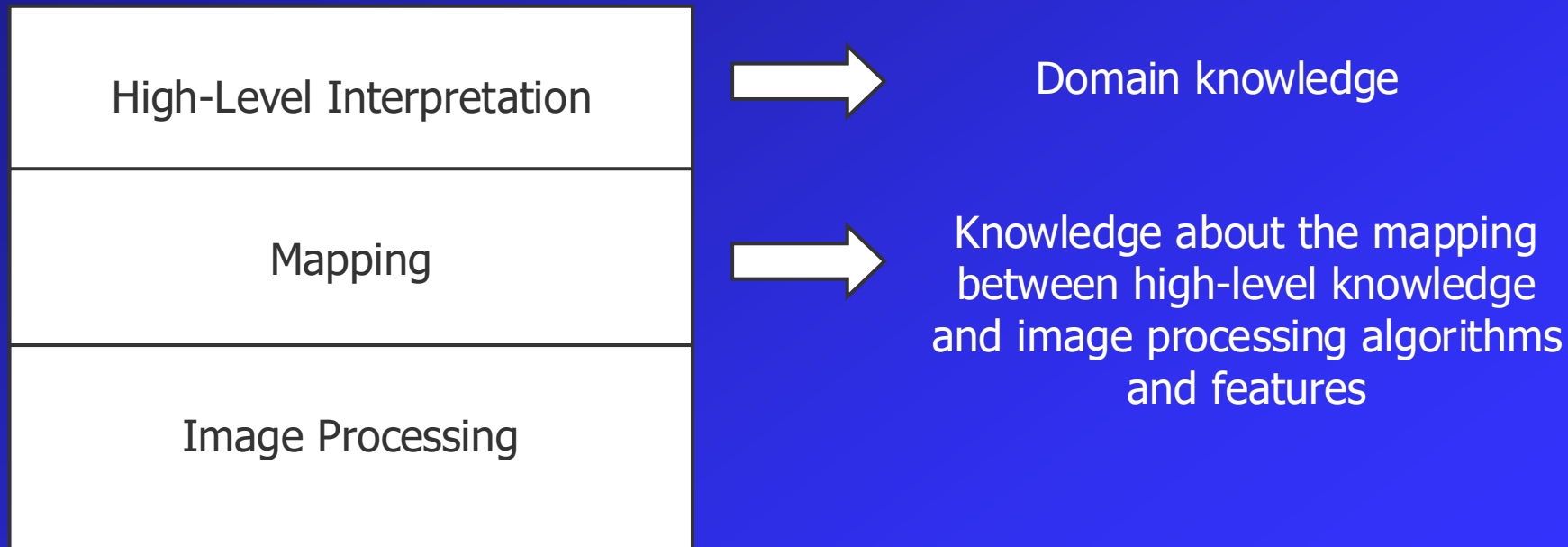
- Assigning a category (e.g. Aircraft, Galaxy) to a region of the image
- Categories are discrete entities characterized by properties shared by their members

Introduction: Goal

- **Goal:** Enabling experts to build object categorization systems dedicated to his/her domain of interest (e.g. biologist, astronomer)
- **Issues:**
 - Knowledge acquisition
 - Semantic gap
 - Use of acquired knowledge for performing object categorization
- **Restricted scope:**
 - One object per image
 - Application domains with well-defined expertise

Introduction: Proposed Approach

- *Proposed Approach*: decomposition of the object categorization problem in **three** levels of abstraction [Marr82]



Introduction: Proposed Approach

Use of **ontological engineering** combined with **machine learning techniques**



- Reduction of the knowledge acquisition problem and of the semantic gap
- Performing categorization as experts do

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State of the Art : Object Recognition

- Geometric Methods [*Faugeras 93*]

➡ Model alignment

- [*Brooks83*] Object modeling by ribbons. Geometric reasoning
- [*Grimson90*] Generalized Hough transform used for recognizing objects from noisy data
- [*Basri96*] Combination of alignment method with recognition by **prototypes**
- [*Sangineto03*] Classification based on the notion of **geometric abstraction**

State of the Art : Object Recognition

- Appearance-Based Methods

➔ Objects models not explicit
Use of multiple views

- *[Swain91]* Objects represented by color histograms
- *[Schmid97]* Local features. Introduction of a voting algorithm
- *[Schiele00]* Receptive field histograms for approximating the local appearance
- *[Fergus03]* Local features. Objects modeled as constellations of parts

State of the Art : Object Recognition

- Knowledge-Based Methods [*Crevier97*]
 - [*Draper89*] Blackboard architecture. Schemas (frames + procedures). Schema instantiation, hypothesize and test cycle
 - [*Matsuyama90*] Three expert systems. Frames + rules. Both model driven and data driven. hypotheses generation/verification.
 - [*Hudelot05*] Cooperation between three knowledge-based systems (Frames + rules). Data management functionalities.

State of the Art : Object Recognition

■ Summary:

■ Geometric Methods

- + Strong theoretical foundations
- Generalization difficult
- Reliable Extraction of geometric primitives is very difficult

■ Knowledge-Based Methods

- ⇒ + Explicitness
- ⇒ + Separation between knowledge and reasoning
- Knowledge acquisition bottleneck

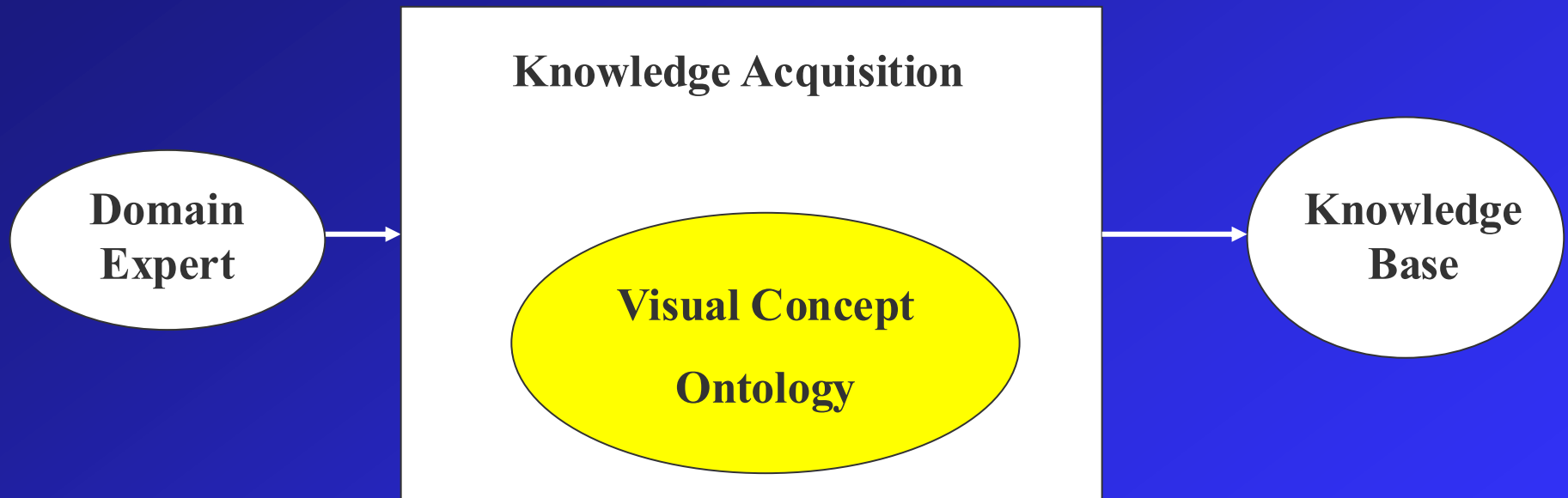
■ Appearance-Based Methods

- ⇒ + Very efficient ...
- ... Provided that enough samples are available
- Management of invariance
- Lack of explicitness



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Knowledge Acquisition



Knowledge acquisition **guided** by a **visual concept ontology** (i.e. *geometry, texture, color*) to describe the objects of the domain.

Knowledge Acquisition

- **Ontology** :
 - Definition: An explicit specification of a conceptualization [*Gruber93*]
 - Composed of:
 - A set of concepts
 - A set of relations between concepts
 - A set of axioms (e.g. transitivity, reflexivity)
 - Ontological Commitment [*Bachimont2000*]
 - ➡ Shared reference to align with

■ Visual Concept Ontology

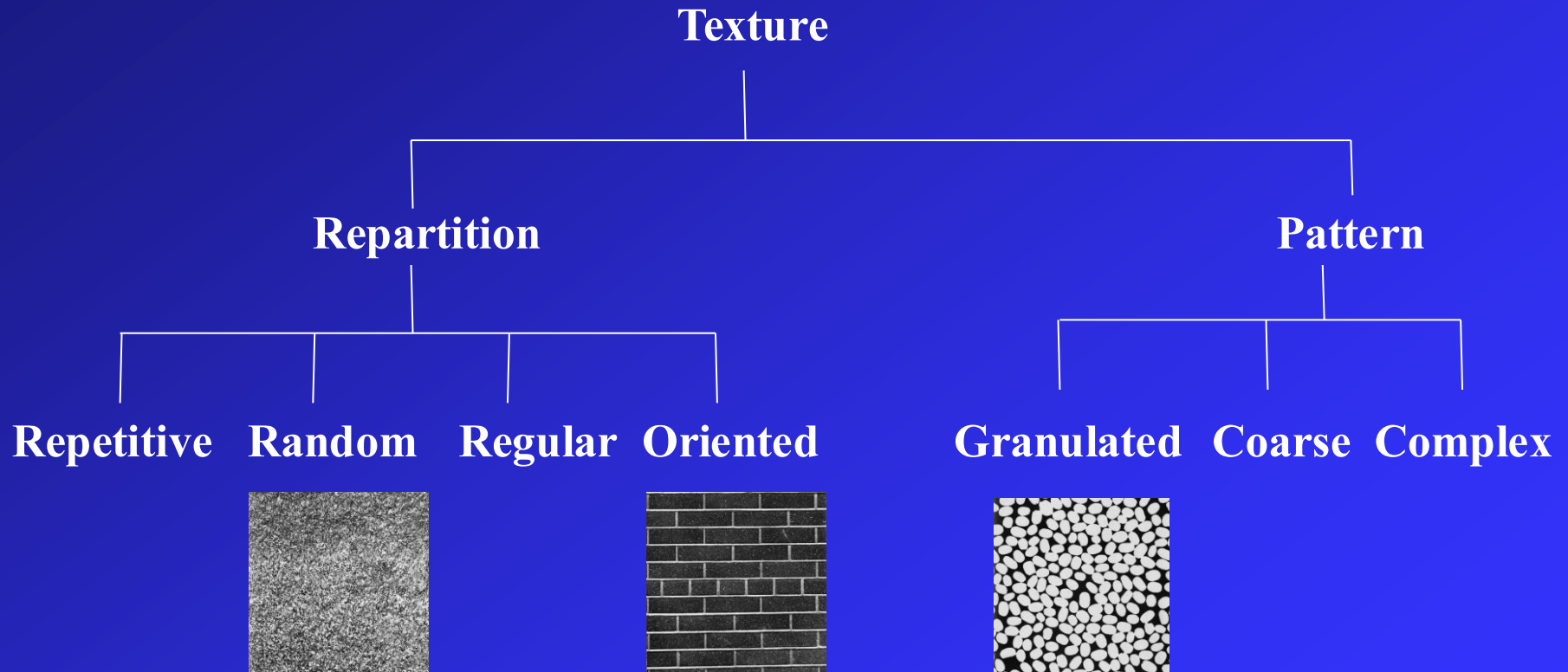
■ 144 concepts :

- spatial concepts (geometry, size, position, orientation)
- color concepts (hue, brightness, saturation)
- texture concepts (pattern, contrast, repartition)

➡ Object classes are described by **visual concepts**

Knowledge Acquisition

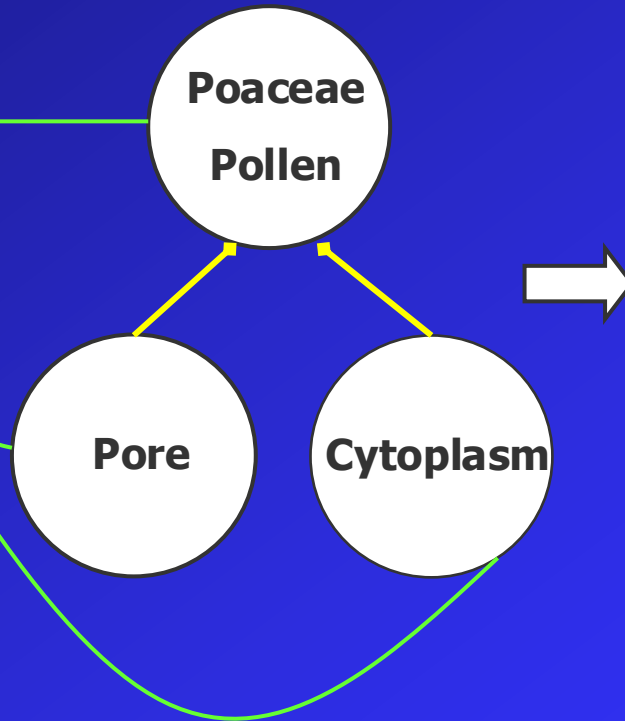
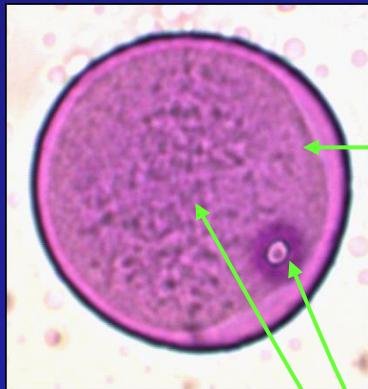
Visual concept ontology content: some **texture concepts**



➡ Based on cognitive experiments [Bhushan et al 97]

Knowledge Acquisition

Domain knowledge described using
visual concept ontology



Poaceae :

- **Circular Shape**
- **Granulated Texture**
- **Pink Color**

Pore:

- Subpart of **Poaceae**
- **Elliptic Shape**
- **Small Size**

Subpart Tree

Knowledge Acquisition

- Knowledge Formalization
 - Domain Taxonomy: specialization relations
 - Domain Partonomy: subparts linked to domain classes
 - Class: a category (*aircraft, pollen grain*) described by visual concepts (*pink color and circular shape*)
 - Representation by frames with slots

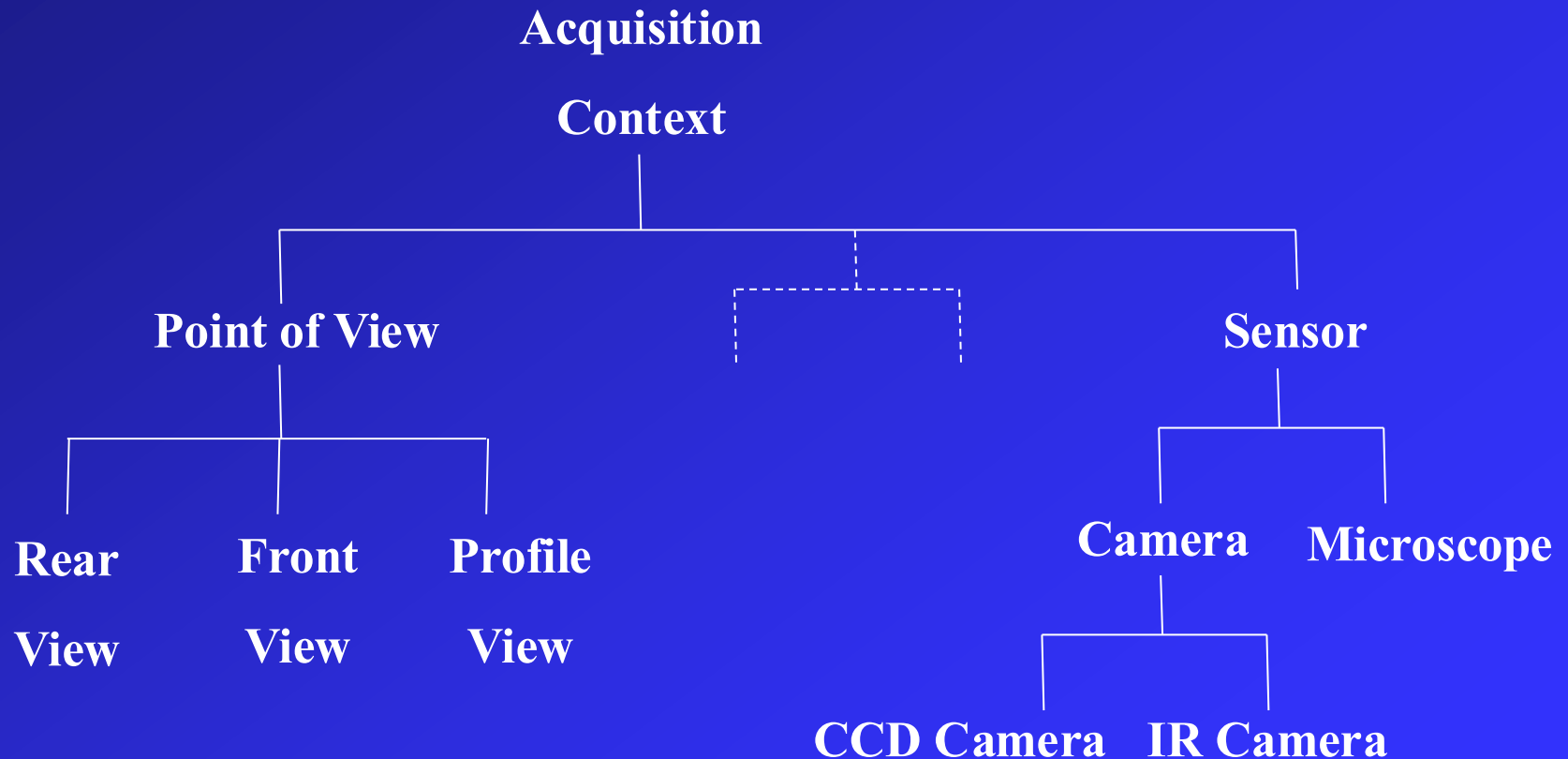
Phase 1: Knowledge Acquisition

Each visual concept is associated with numerical features:

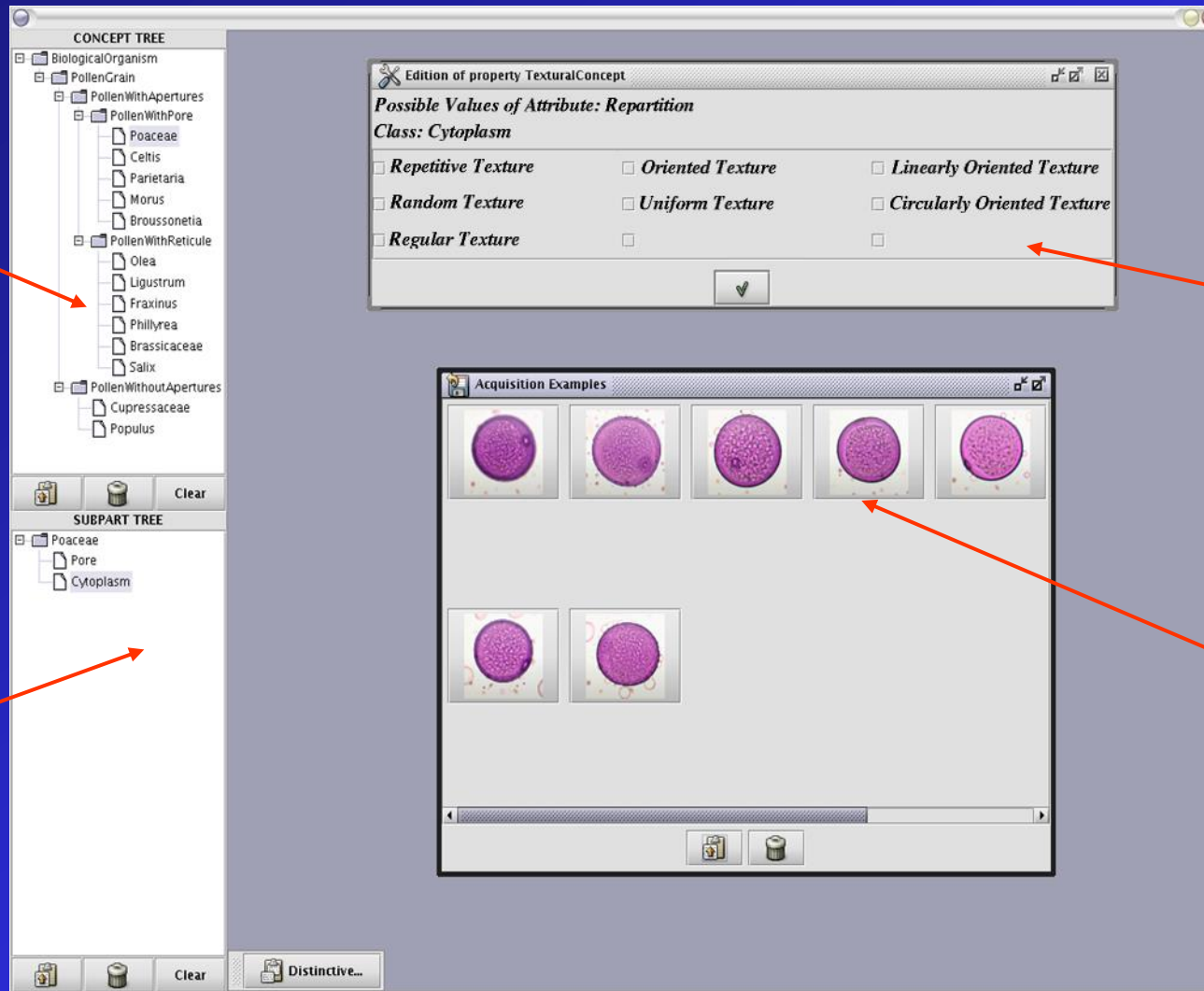
Visual Concept	Examples	Numerical Features
Shape	Polygonal, Straight	SIFT Features
Texture	Granulated, Smooth	Gabor Features Co-Occurrence Matrices
Color	Blue, Bright, Dark	Histograms Color Coherence Vectors

Knowledge Acquisition

- Importance of acquisition context
 - Visual description is valid for a given acquisition context



Knowledge Acquisition



Domain
class
hierarchy

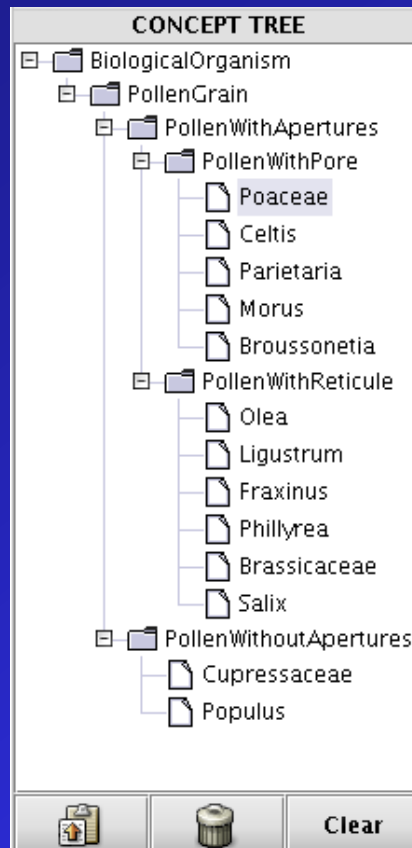
Ontology
driven
description

Subparts
hierarchy

Image
samples
management

Knowledge Acquisition

Domain knowledge acquisition



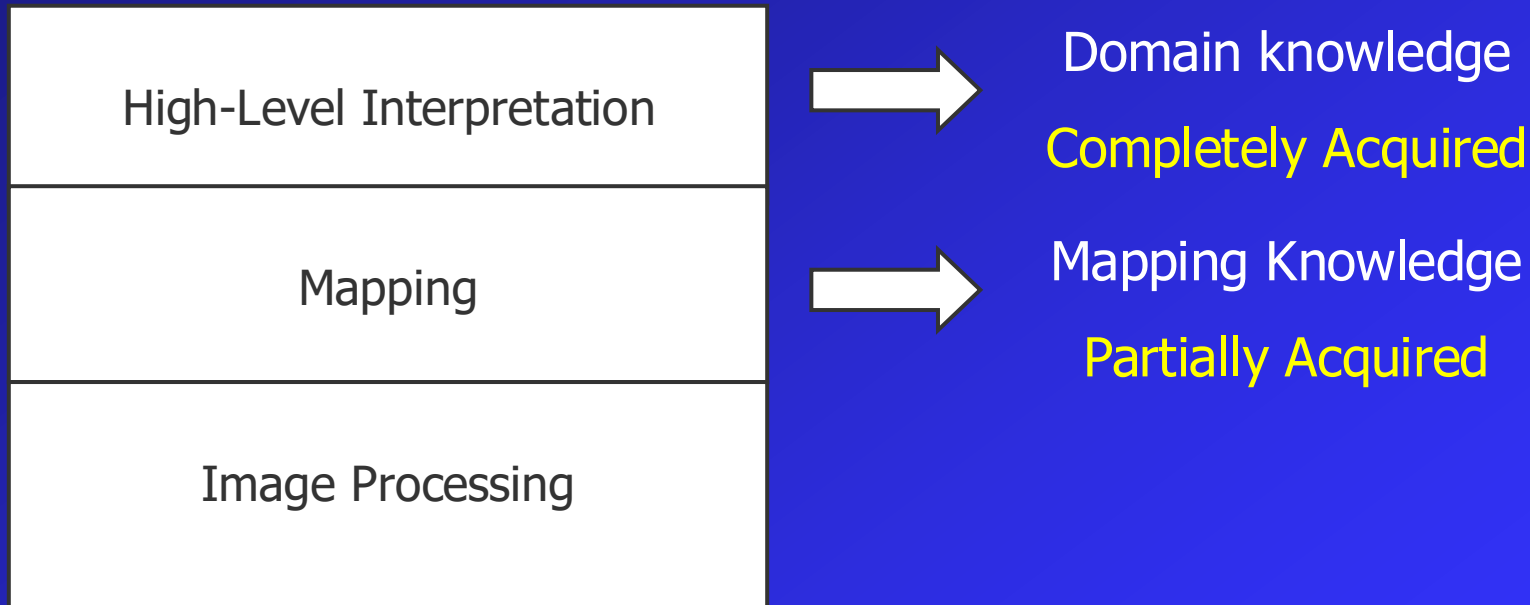
Domain class hierarchy



Subpart hierarchy

Knowledge Acquisition

- Conclusion:

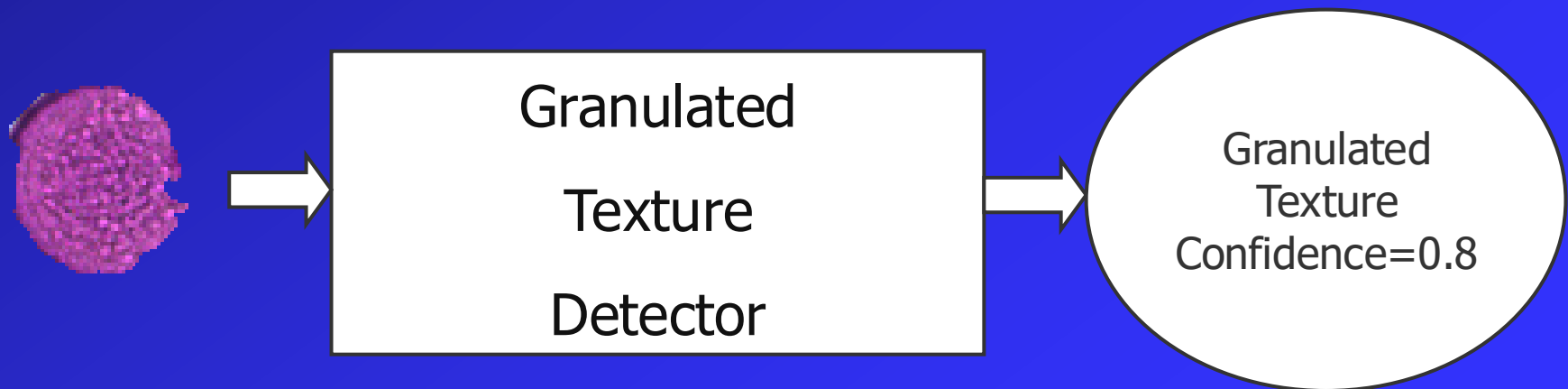


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Visual Concept Learning

- Visual Concept Learning
 - **Goal:** Producing **visual concept detectors**
 - **Why:** Completing mapping knowledge
 - **How:** Training of Support Vector Machines (SVM) with **annotated samples**



Visual Concept Learning

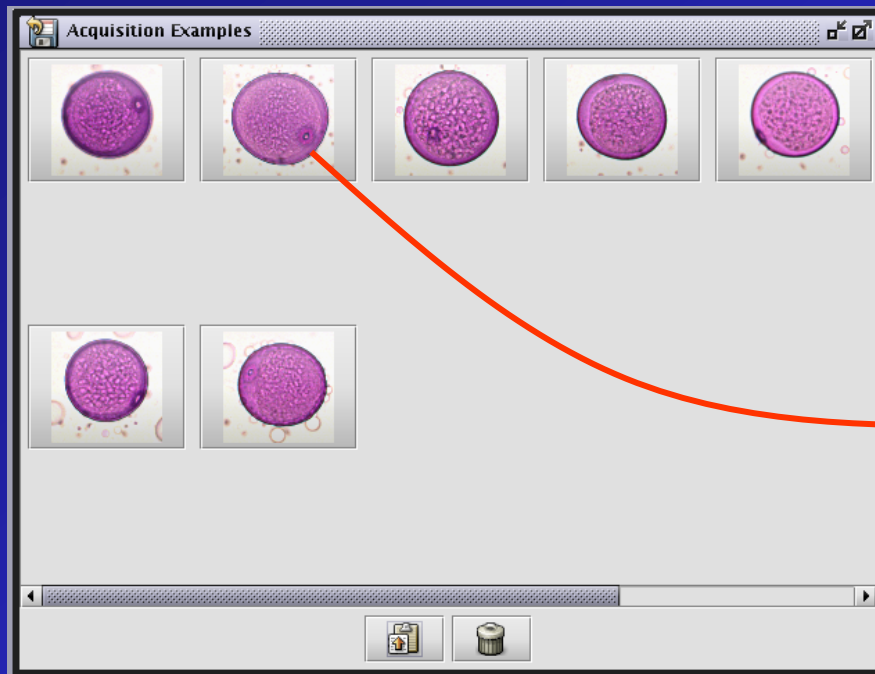
Image Samples Segmentation and Annotation
by **visual concepts**

Goal: Obtaining annotated image regions for
enabling visual concept learning

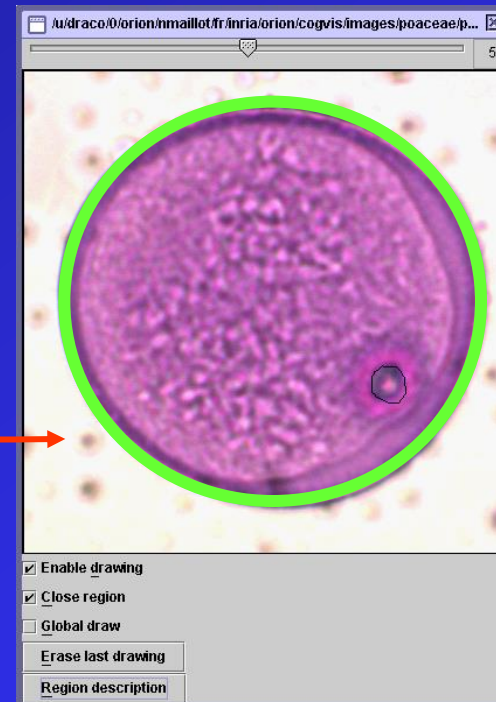
- Manual approach
- Use of 3-D models
- Weakly-supervised approach

Visual Concept Learning

- Image Samples Segmentation and Annotation: **Manual Approach**



Selection of an example of Poaceae object



Interactive selection of region of interest with a drawing tool

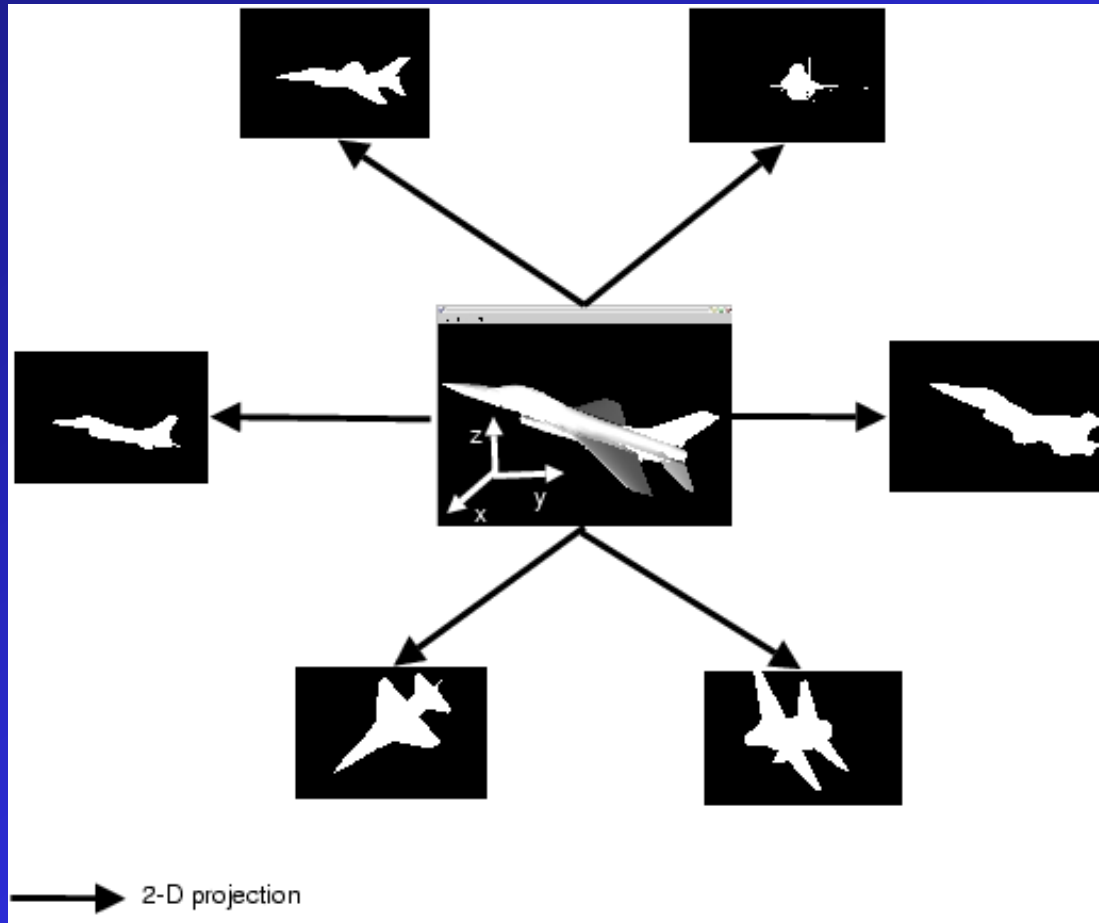
Annotation of selected region

by visual concepts:

- Pink
- Large
- Circular

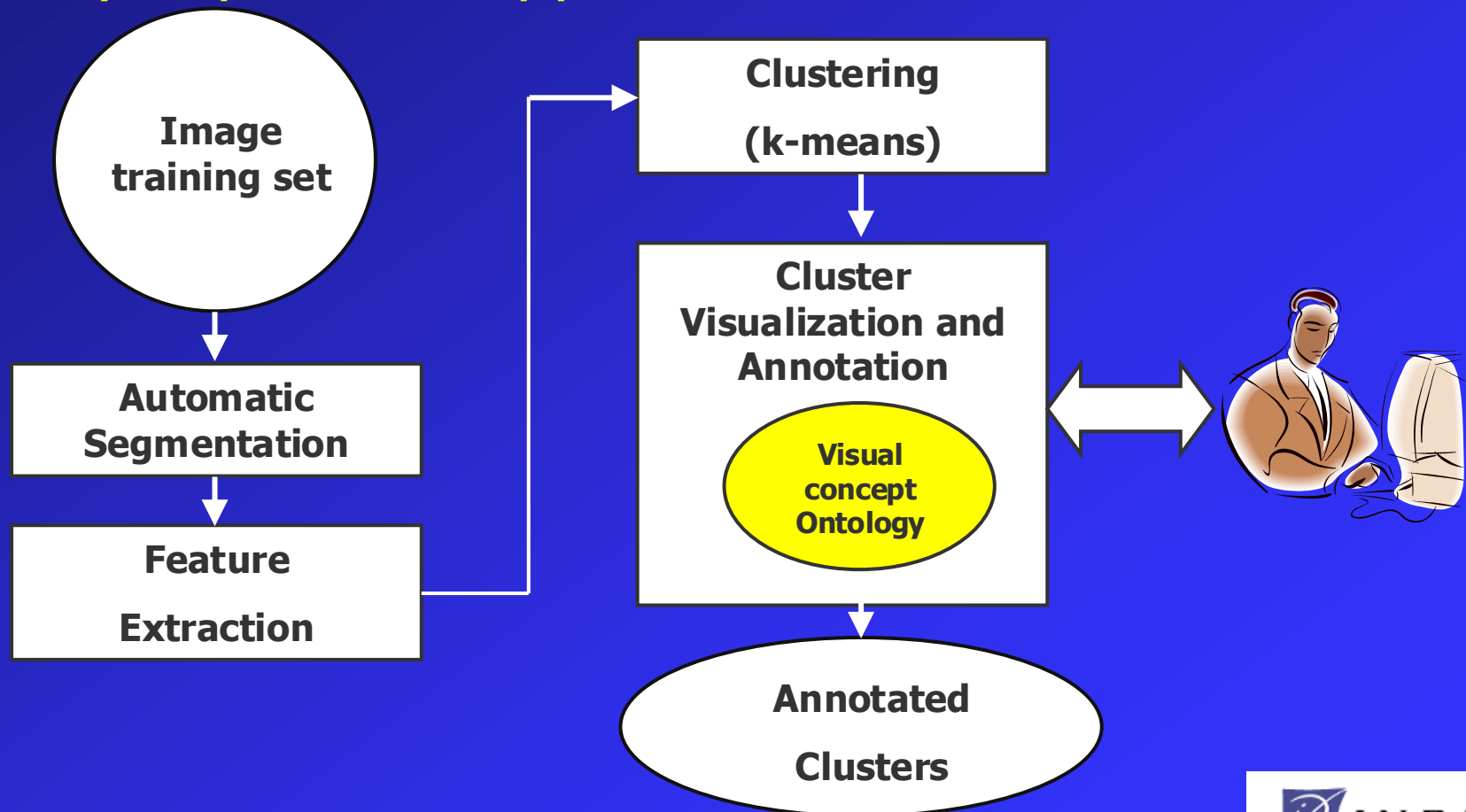
Visual Concept Learning

- Image Samples Segmentation and Annotation: Use of 3-D Models (meshes)



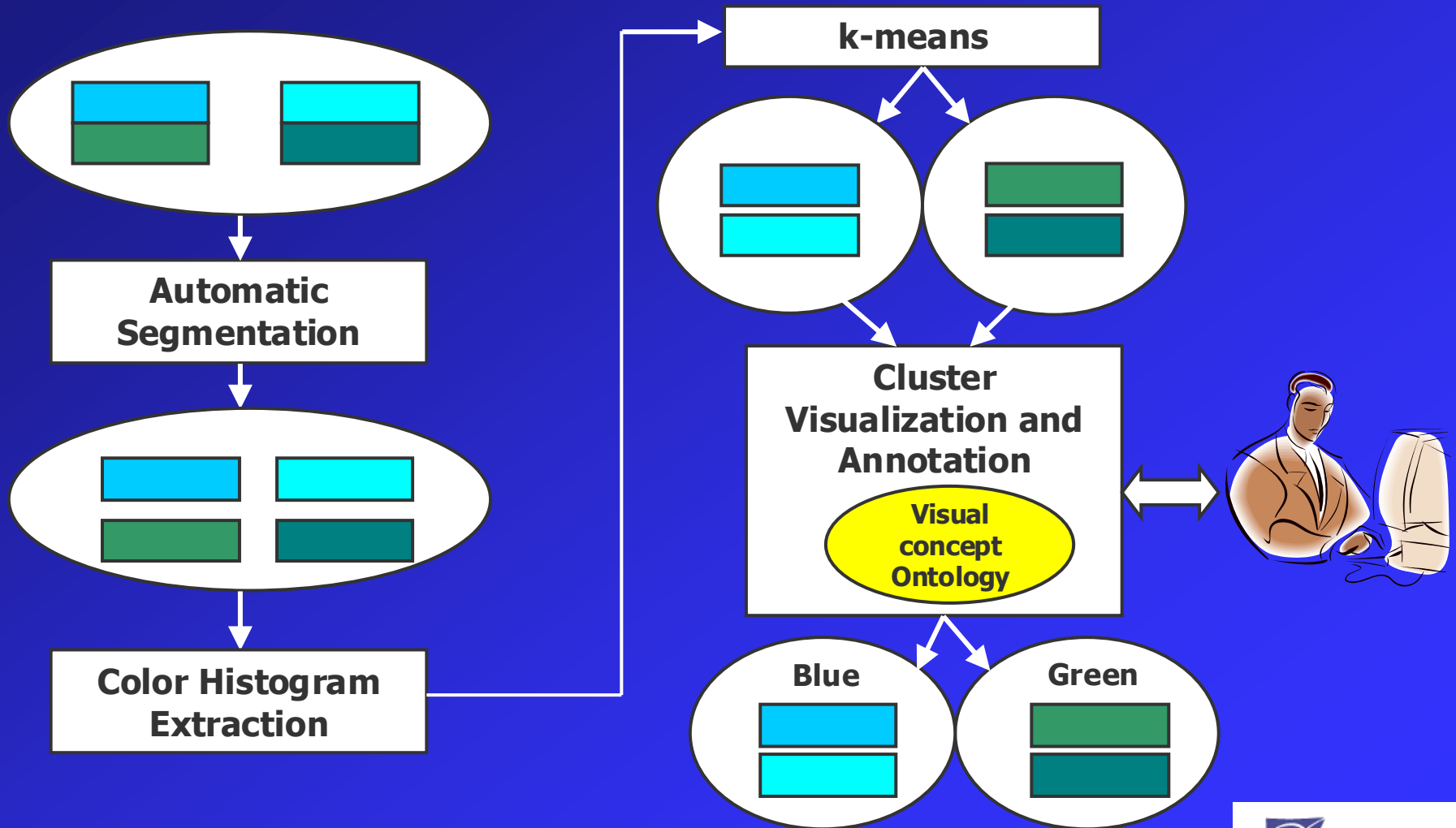
Visual Concept Learning

- Image Samples Segmentation and Annotation:
weakly-supervised approach



Visual Concept Learning

Example: clustering for visual concept category **Hue**



Visual Concept Learning

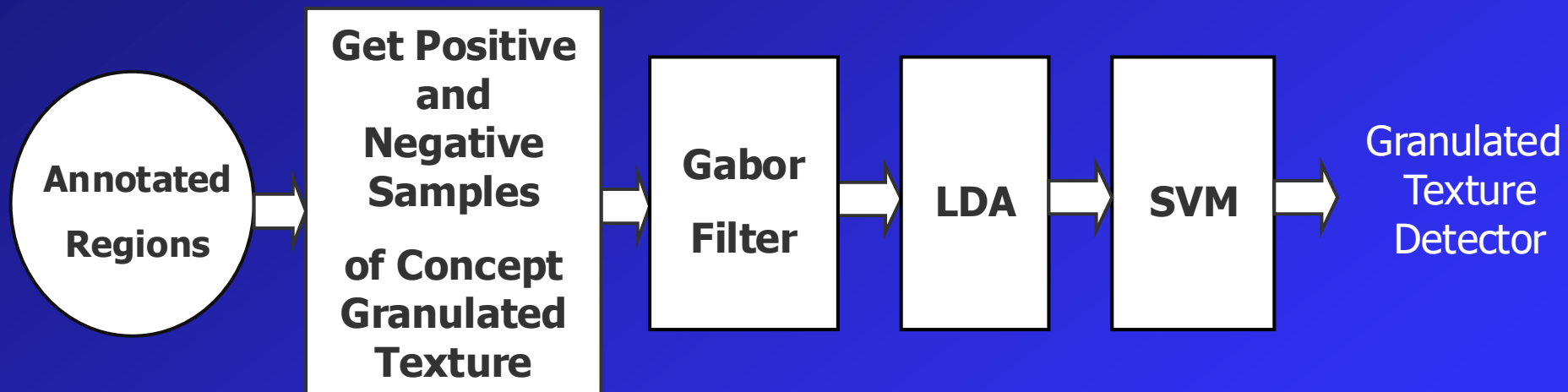
Learning (for all visual concept C used during knowledge acquisition)



➡ SVM based on Radial Basis Function Kernels

Visual Concept Learning

Example : Learn the visual concept Granulated Texture



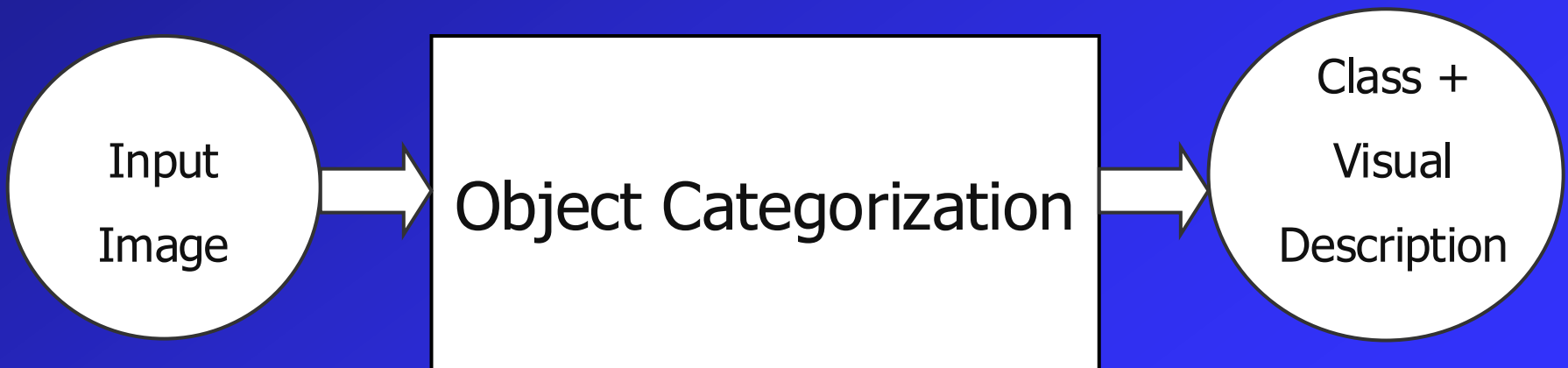
Visual concept detectors are used to **complete** the mapping knowledge

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Object Categorization

- Object categorization based on:
 - Acquired Knowledge (domain knowledge + mapping knowledge)
 - Visual concept detectors
- Mechanism: Hypothesis Generation/Verification



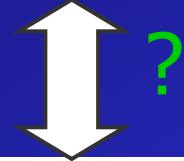
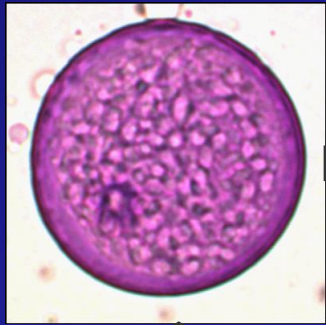
Object Categorization

Algorithm: Hierarchical exploration of object classes

- For each class of the class hierarchy from root class
- **Detection** in the segmented image of the visual concepts used to describe the class
- **Local matching** between each visual concept of the class and visual concepts detected in the image
- **Recursion** on sub-parts
- **Global Matching** (object/class)
- If compatibility then consider sub-classes
else Back-track

Object Categorization

Object to Categorize



Current Hypothesis:

Poaceae :

- *Circular Shape*
- *Granulated Texture*
- *Pink Hue*

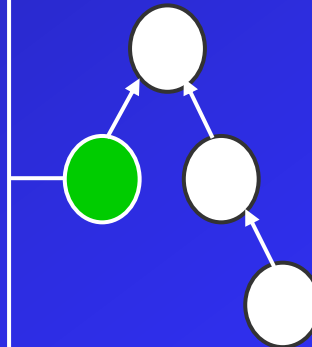
**Automatic
Segmentation**

**Feature
Extraction**

**Circular
Shape
Detector**

**Granulated
Texture
Detector**

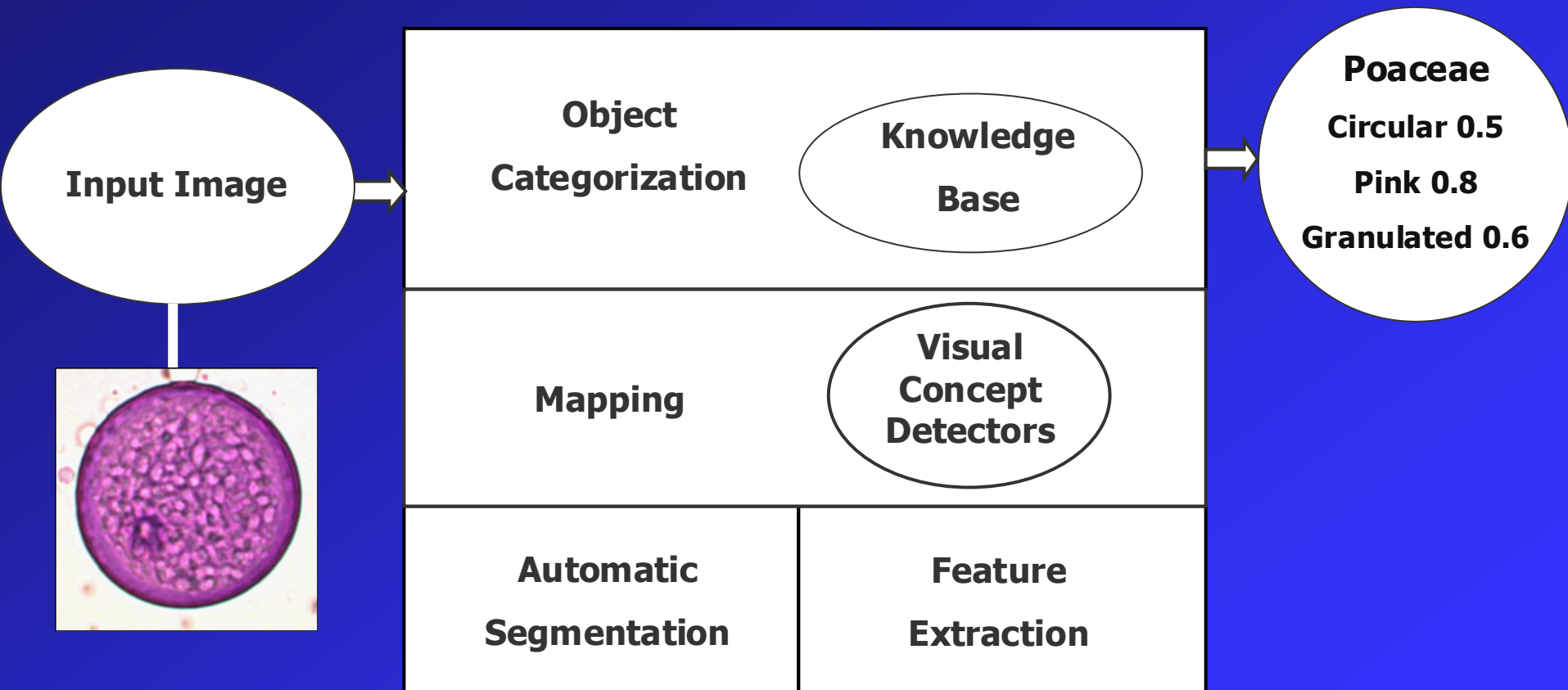
**Pink Hue
Detector**



X

Confidence Value

Object Categorization



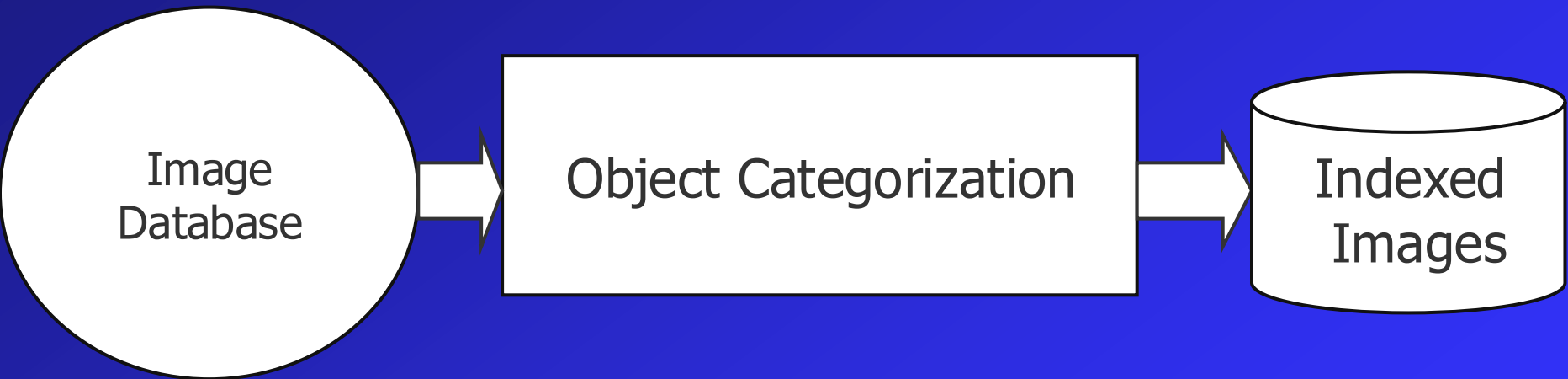
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Results

- **Application:** Semantic image indexing and retrieval
- **Domain:** Transport Vehicles (aircraft, motorbikes, cars) in their environment
- **Goal:** Enabling Retrieval/Indexing by concept
 - User-friendliness
 - Efficiency: no need to store pre-computed feature vectors
- **Issue:** trade off between **semantic richness** and **amount of work** needed to build semantic indexing and retrieval systems

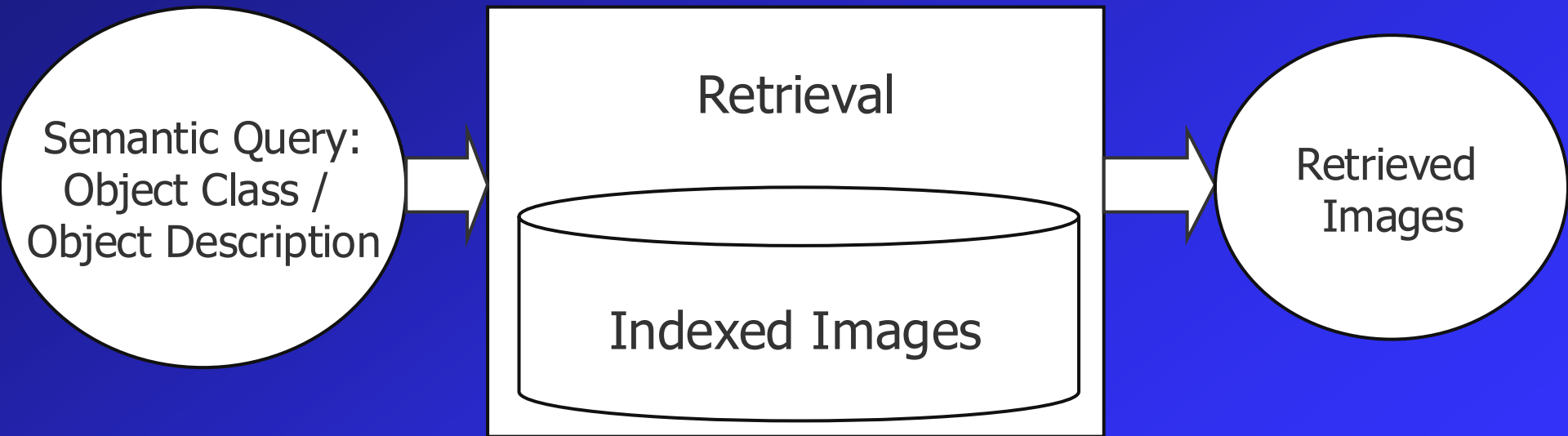
Semantic Indexing



➡ Use of categorization results as index for images

Results

Query by concept (opposed to query by example):



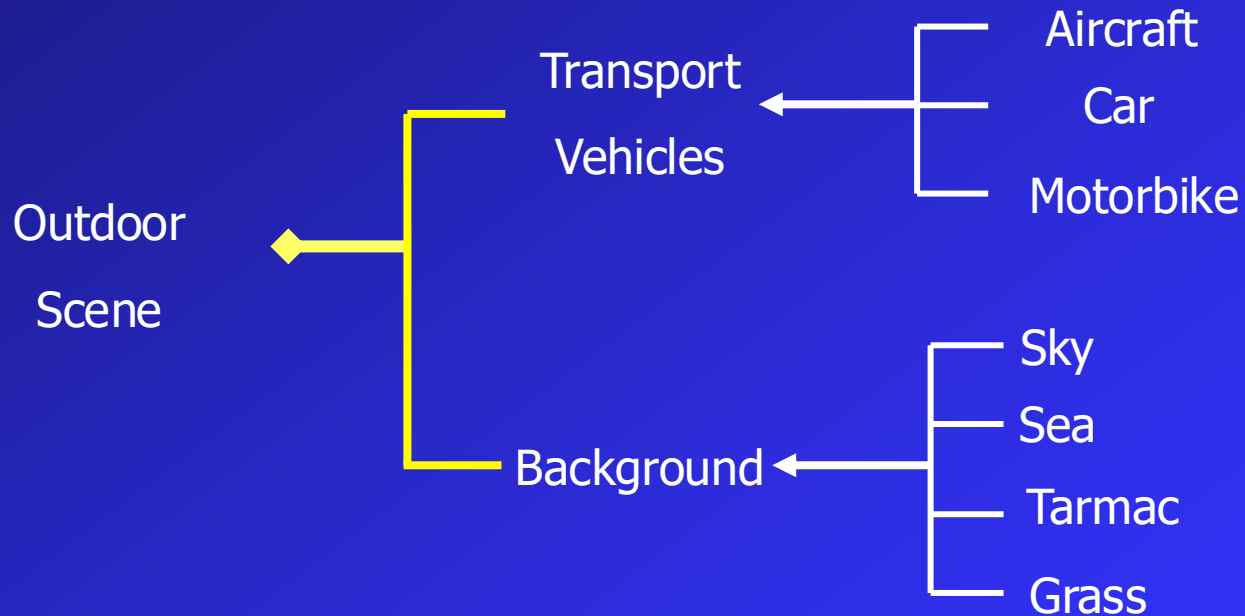
- Example of semantic queries : "Aircraft ", "Gray Aircraft and Blue Sky"

Results

- [Fauqueur03] Retrieval/Indexing based on region templates
 - [Town04] **Supervised** learning used for mapping image data to a domain ontology
 - [Mezaris04] Querying based on an object ontology (color, position, size, shape). Machine learning and user feedback are used for improving system efficiency
- ➡ No approach combines **weak supervision** with a **rich high-level knowledge layer**

Results

Knowledge acquisition



→ Composition Link

→ Specialization Link

Results

Knowledge acquisition

	Hue	Brightness	Geometry	Position	Pattern
Aircraft			Polygonal	Center	
Car			Polygonal	Center	
Motorbike			Polygonal	Center	
Sky	Blue Grey	Dark Light		Top	Smooth
Tarmac	Grey Black			Bottom	Uniform
Grass	Green			Bottom	Uniform

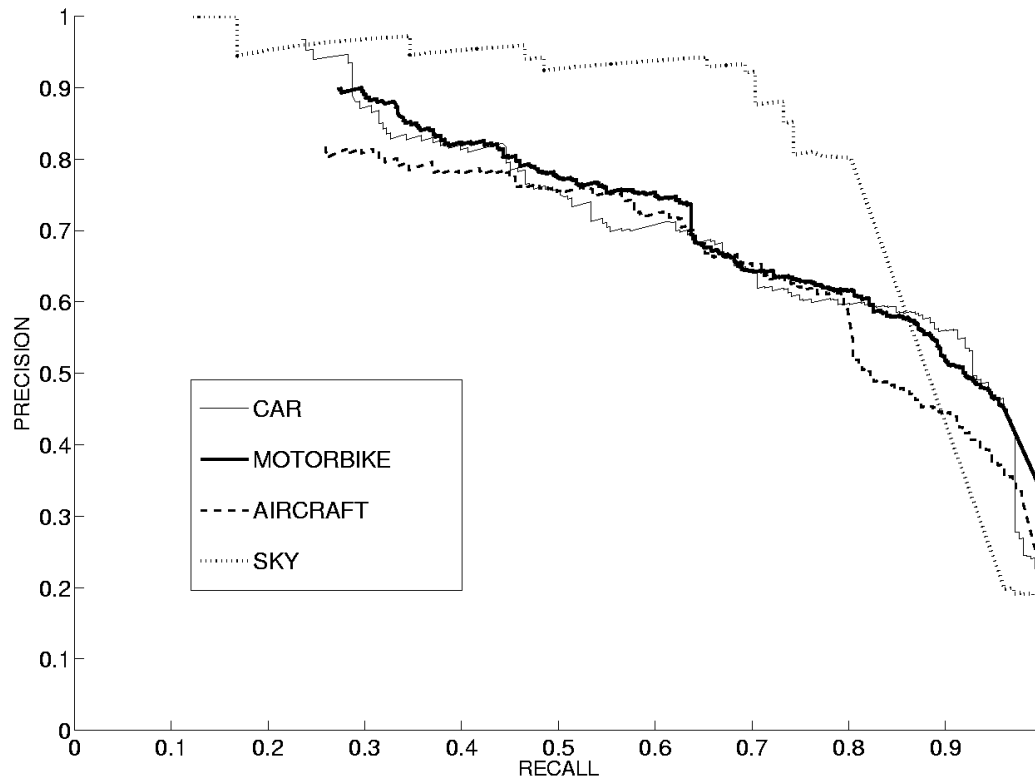
Results

- Training Set : 850 images (aircraft, car, motorbike, sky)
- Test Set : 2000 images (contains 300 images of each class and 800 background images)



Results

- Results : Precision/ Recall Curve



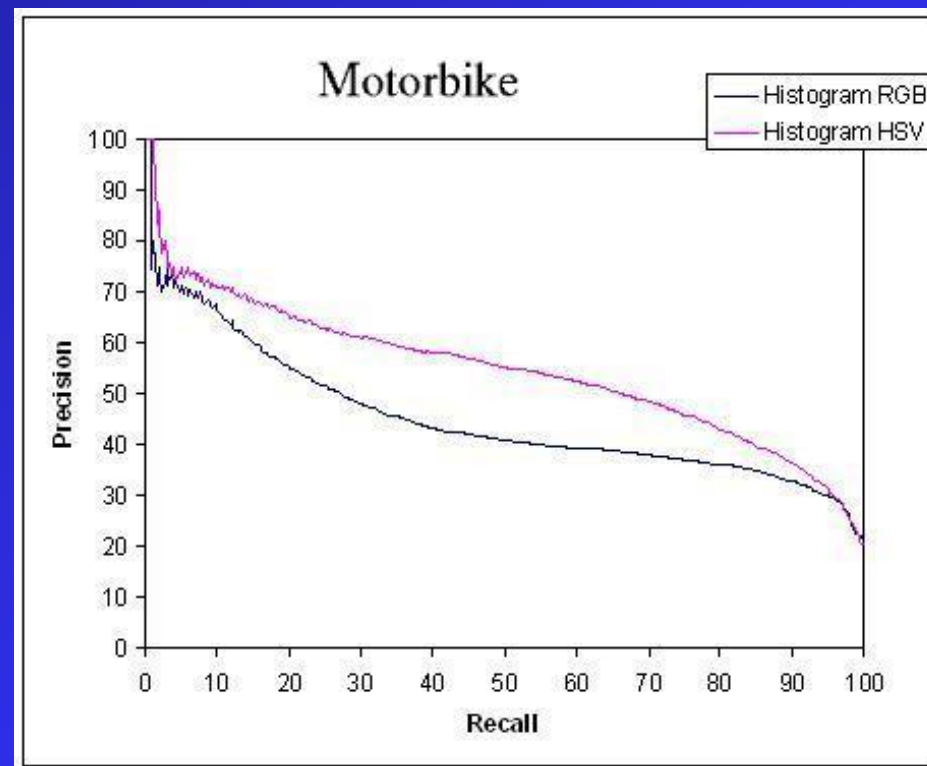
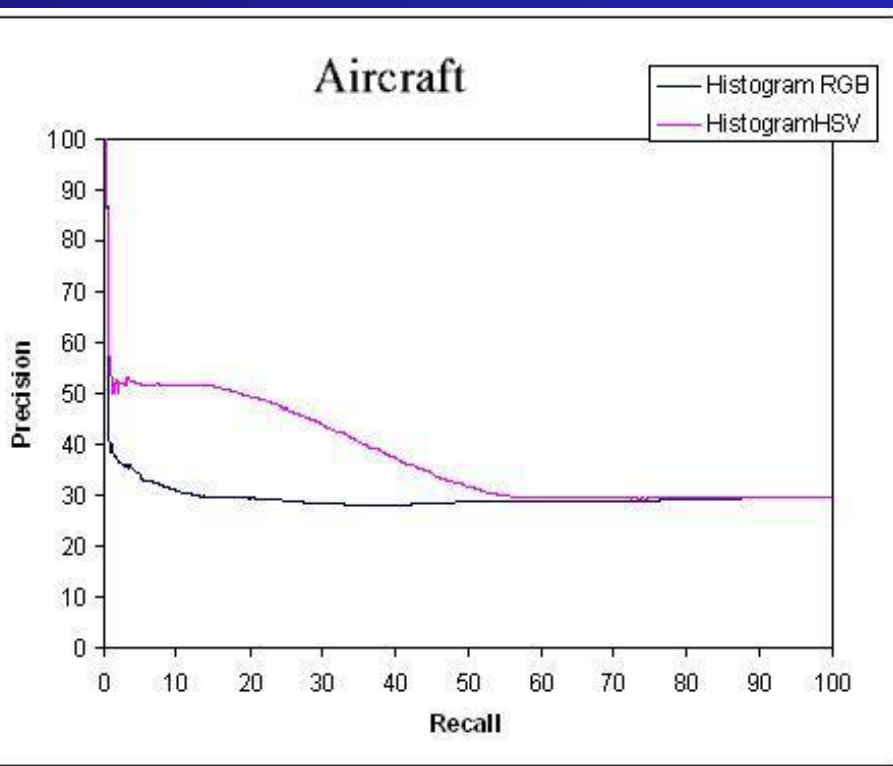
- Recall=50%
- Precision=75%-90%

Precision = $\frac{\#(\text{relevant retrieved images})}{\#(\text{retrieved images})}$

Recall = $\frac{\#(\text{relevant retrieved images})}{\#(\text{relevant images})}$

Results

Retrieval and Indexing by query by example



- ➔
- Recall=50%
 - Precision=32%-55%

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Conclusion

- **Approach** : semantic object categorization

Three phases:

1. Knowledge acquisition
2. Visual concept learning
3. Object Categorization

- **Application**: Semantic image indexing and retrieval

Conclusion

- Contributions:
 - An **extendible** and **reusable** visual concept ontology
 - A knowledge acquisition methodology
 - can for other purposes than computer vision (e.g. biological knowledge capitalization)
 - Original signal/semantics integration approach
 - clear distinction of the mapping problem
 - no inference rules to define manually
 - An object categorization algorithm

Future Works

- Integration of **data management** functionalities *[Hudelot 05]*
 - Spatial reasoning
- Learning for **adaptive** image segmentation *[Martin et al. 06]*
- Extension to video content
- Dynamic knowledge bases
- Integration of elements geometry based approaches

Publications

[1] Ontology Based Complex Object Recognition

N. Maillot, M. Thonnat

Image and Vision Computing Journal

Under Minor Revision

[2] Towards Ontology Based Cognitive Vision (Long Version)

N. Maillot, M. Thonnat, A. Boucher

Machine Vision and Applications Journal (MVA)

Springer-Verlag Heidelberg, December 2004, 16(1), pp 33--40

[3] A Weakly Supervised Approach for Semantic Image Indexing and Retrieval

N. Maillot, M. Thonnat

International Conference on Image and Video Retrieval (CIVR 2005)

Singapore, 20-22 July 2005

[4] Ontology Based Object Learning and Recognition : Application to Image Retrieval

N. Maillot, M. Thonnat, C. Hudelot

16th IEEE International Conference on Tools for Artificial Intelligence (ICTAI 2004)

Boca Raton, Florida, 15-17 November 2004

[5] Towards Ontology Based Cognitive Vision

N. Maillot, M. Thonnat, A. Boucher

Third International Conference on Computer Vision Systems (ICVS 2003)

Graz, Austria, April 2003, LNCS 2626, pp.44-53, Springer-Verlag Berlin Heidelberg 2003