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Towards Ontology Based Cognitive Vision

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Abstract This paper details a visual concept ontology driven knowledge acquisition methodology. We propose to use a visual concept ontology to guide experts in the visual description of the objects of their domain (e.g. pollen grain).

The proposed knowledge acquisition process results in a knowledge base which can be used by a knowledge based vision system. An important benefit of our approach is that the knowledge acquisition process guided by the ontology leads to a knowledge base close to low-level vision.

A visual concept ontology and a dedicated knowledge acquisition tool have been developed and are presented. We propose a generic methodology that is not linked to any application domain. An example shows how the knowledge acquisition model can be applied to the description of pollen grain images.

keywords: cognitive vision – ontological engineering – knowledge-based vision.

1 Introduction

Our goal is semantic image interpretation for complex object classification purposes. The difficulty of semantic image interpretation can be illustrated by Fig. 1. Indeed, this image can be interpreted as a light object on a dark background. One can also see an astronomical object and more precisely a spiral galaxy. This illustrates that semantic interpretation relies on a priori knowledge.

Many knowledge-based vision systems have been suggested in the past (VISIONS (Hanson et al. 1987), SCHEMA (Draper et al. 1989), SIGMA (Matsuyama et al. 1990) , SYGAL and PROGAL (Thonnat et al. 1989). They all require knowledge bases specifically designed for the ap-

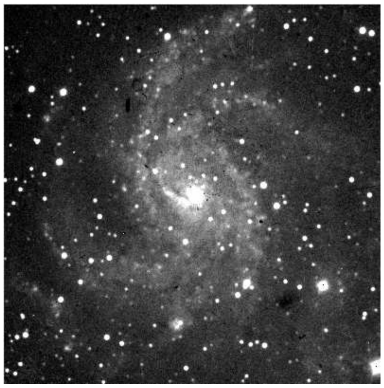

Fig. 1 The semantic interpretation of this image requires a priori knowledge in astronomy

plication domain. As explained in (Draper et al. 1996), designing such knowledge bases is very time consuming. This task also needs multidisciplinary skills. Indeed, both domain knowledge and image processing techniques are involved in this process. Our goal is to acquire domain knowledge without requiring image processing skills.

The long experience of our team in knowledge based vision systems design (Thonnat et al. 1989 ; Liu et al. 1994) also shows that experts often use a partially shared vocabulary for describing the objects of their domain.

We propose an approach based on results originating from the ontological engineering community. We propose to use a visual concept ontology to hide the low-level vision layer complexity and to guide the expert in the description of the objects of his/her domain. Then, we want to build knowledge bases relying on the visual concept ontology. Our approach is different from ontology-based image retrieval techniques where a domain-dependent ontology is used to annotate images. For instance, in (Von-Wum et al. 2002) retrieval is based on domain related annotations and not on a visual concept ontology.

Section 2 introduces the reader to ontological engineering. Section 3 gives an overview on our proposed approach. Section 4 is dedicated to the knowledge acquisition process we propose. Section 5 presents an ontology composed of three different types of visual concepts : texture concepts, color concepts and spatial concepts. Section 6 shows how the proposed ontology can be used for describing objects from a specific domain. Finally, Section 7 details the features of the specific knowledge acquisition tool we have developed and used for the description of several pollen grains types.

2 Ontological Engineering

Gruber defines the notion of ontology in (Gruber 1993): "An ontology is an explicit specification of a conceptualization".

As explained by Bachimont (see (Gandon 2002)), the aim of ontologies is to define which primitives, with their associated semantics, are necessary for knowledge representation in a given context.

An ontology is composed of several entities:

- a set of concepts (C) (e.g. geometric concepts)
- a set of relations(R) (e.g. spatial relations)
- a set of axioms (e.g. transitivity, reflexivity, symmetry of relations)

Two partial orders $\preceq_C$ and $\preceq_R$ define the concept hierarchy and the relation hierarchy, respectively. An ontology is supposed to be the support of reasoning mechanisms.

To be efficient, communication between people and software systems must rely on a shared understanding. As explained in (Gandon 2002), lack of shared understanding leads to difficulties in identifying requirements and to limited inter-operability or reusability. These problems are often met when building or interacting with computer vision systems. Ontologies are a common base to build on and a shared reference to align with (Gandon 2002). This shared reference is obtained by a consensus called ontological commitment. That is why ontological engineering can be useful for the cognitive vision community.

As explained in (Blazquez et al. 1998), ontology development process has to be done in four distinct phases.

- the first one is called specification and states why the ontology is built and who are the end-users
- the next phase is conceptualization and leads to a structured domain knowledge
- then comes the formalization phase that transforms the conceptual model into a formal model
- finally, implementation transforms the formal model into a computational model

This methodology has been used to design the visual concept ontology presented in section 5.

3 Proposed Approach

As described in (Matsuyama et al. 1990), several types of knowledge can be identified in knowledge-based vision systems (Fig. 2):

1. domain knowledge
2. knowledge about the mapping between domain knowledge and image processing knowledge
3. image processing knowledge

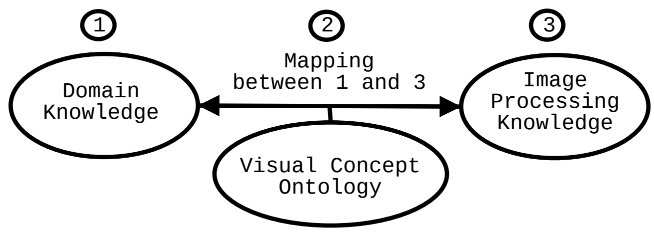

Fig. 2 The visual concept ontology reduces the semantic gap between domain knowledge and image processing knowledge

Our work is focused on the mapping between domain knowledge and image processing knowledge. Extracting domain knowledge means producing a hierarchical structure of domain object classes associated with their subparts (Fig. 3).

This knowledge belongs to the domain of interest and is shared by the specialists of the domain (e.g. biologists, astronomers). It is important to note that domain knowledge is independant of any vision layer and can be reused for other purposes.

In our approach, the mapping between the domain and the image is based on a visual concept ontology. Ontological concepts are linked both to domain knowledge and to low-level vision numerical descriptors.

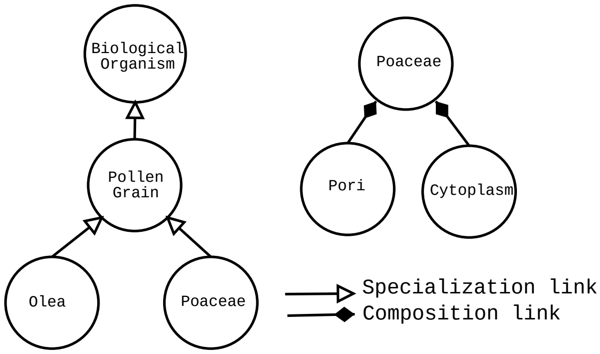

Fig. 3 Domain knowledge structure: on the left, a hierarchy of classes, on the right a subpart tree

This ontology can be considered as a guide which provides the vocabulary for the visual description of domain classes.

4 Overview of the Knowledge Acquisition Process

As described in Fig. 4, the proposed knowledge acquisition process is guided by the visual concept ontology. The expert starts by producing domain knowledge which is structured as a hierarchy of domain classes with their subparts. Then comes the visual concept ontology-driven description phase, which means that the expert uses the vocabulary provided by the ontology to describe the objects of the domain. This task is performed in a user-friendly way with a graphical user interface. The result of the description phase is a knowledge base composed of the visual concepts provided by the ontology associated with domain classes. For example, the visual concept *Circular Surface* provided by the ontology can be used to describe the shape of a domain object.

Domain object samples are also provided. A user interface is used to provide these samples.

5 A Visual Concept Ontology

In this section, we propose a visual concept ontology. This ontology can be considered as a guide which provides a vocabulary for the visual description of domain classes. It is important to note that the proposed ontology is not application-dependent and should be considered as an extendable basis. We have structured this ontology in three main parts. The first one contains texture concepts, the second one contains color concepts and the last one is made of spatial concepts. Each part of this ontology is detailed in the next subsections.

5.1 Texture Concepts

This part of the ontology has been inspired by results from the cognitive science community.

The experiment conducted in (Rao et al. 1993) and (Bhushan et al. 1997) identifies three main dimensions in the texture perception cognitive process. Each perceptual dimension constitutes an important element in texture perception. Each perceptual dimension is seen as an abstraction of a set of texture visual concepts (Fig. 5). From this study, we have built an ontology of texture concepts. Note that quantifiers (e.g. *Non*, *Average*, *Strong*) are also integrated in this ontology and can be used to give a finer visual description.

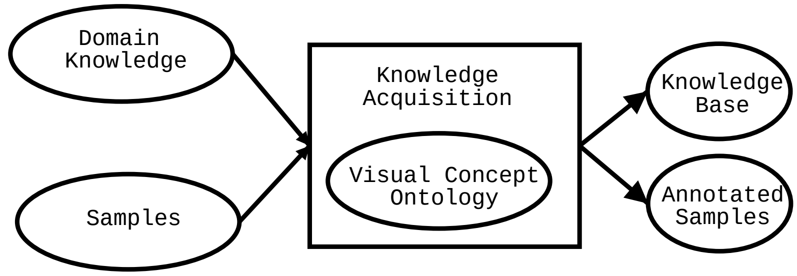

Fig. 4 Knowledge acquisition process: the visual concept ontology guides the knowledge acquisition process. Typical image samples are given as an illustration of domain classes

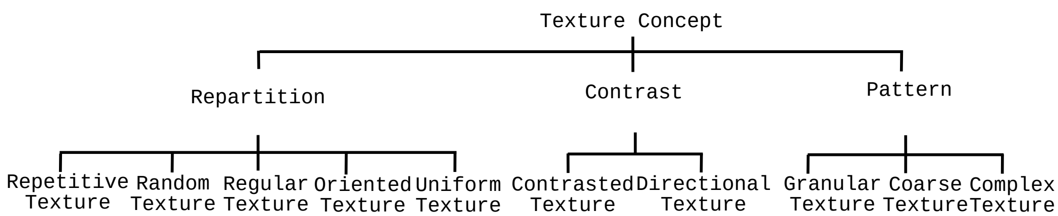

Fig. 5 Texture concept hierarchy

5.2 Color Concepts

This part of the ontology is derived from the ISCC-NBS (Inter-Society Color Council-National Bureau of Standards) color dictionnary. An interesting reflexion on the validity of this dictionnary is given in (Miller et al. 1976). Three kinds of notions are included: hue, brightness and saturation concepts. There are 28 hue concepts (Table 1) which can be combined with five brightness concepts (*Very Dark, Dark, Medium, Light, Very Light*) and four saturation concepts (*Grayish, Moderate, Strong, Vivid*). Certain combinations of brightness and saturation concepts have a perceptual meaning. For instance, the concept *Brillant* is an association of the *Light* and *Strong* concepts. Axioms are contained in the ontology so as to express those kinds of associations.

Red	Purple
Reddish Orange	Reddish Purple
Orange	Purplish Red
Orange Yellow	Purplish Pink
Yellow	Pink
Greenish Yellow	Yellowish Pink
Yellow Green	Brownish Pink
Yellowish Green	Brownish Orange
Green	Reddish Brown
Bluish Green	Brown
Greenish Blue	Yellowish Brown
Blue	Olive Brown
Purplish Blue	Olive
Violet	Olive Green

Table 1 Set of hue concepts

5.3 Spatial Concepts

This part of the ontology is used for describing domain objects from a spatial point of view. A part of the hierarchy is composed of geometric concepts that can be used to describe the shape of domain objects (fig. 6). Three other parts of the ontology contains position, orientation and size concepts. A formalization of a similar approach based on a combination of geometric shapes can be found in (Sciascio et al. 2002). The size of an object can also be described and quantified with a set of quantifiers. Note that quantification can be done both in an absolute and relative way. This means that the size of object A can be described as being important relatively to object B. The notion of elongation is also present and can be quantified. We have also added a set of spatial relations based on the RCC-8 model (Cohn et al. 2001) that can be used to define relations between objects and their subparts.

These relations are enumerated in Table 2 and graphically represented in fig. 7.

RCC-8 relation	Meaning
DC(X,Y)	X disconnected from Y
EC(X,Y)	X externally connected to Y
EQ(X,Y)	X equals Y
PO(X,Y)	X partially overlapping Y
TPP(X,Y)	X tangential proper part of Y
TPP-1(X,Y)	X has tangential proper part Y
NTPP(X,Y)	X nontangential proper part of Y
NTPP-1(X,Y)	X has nontangential proper part Y

Table 2 RCC-8 relations and their meaning

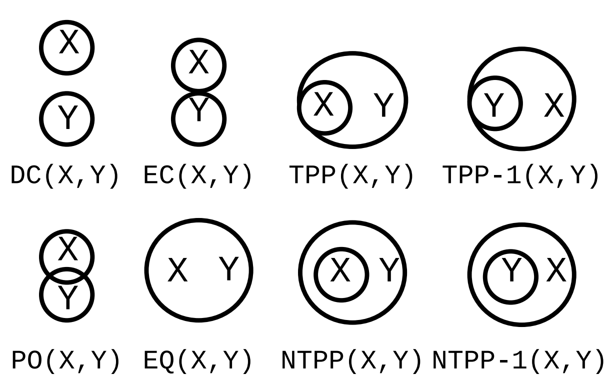

Fig. 7 RCC-8 graphical representation

5.4 Context Description

Experts often observe the objects of their domain in precise observation conditions. For example, when using a microscope, magnification or lighting conditions are controled. Providing contextual information is absolutely necessary. As shown in Fig. 8, context information is the link between domain knowledge and image samples resulting from the acquisition process. Context conditions the resulting acquired images. This implies a relation between the visual description of image samples and the context of acquisition. Context knowledge avoids building incoherent sets of image samples. For instance, it would not make sense to gather images of a similar object acquired with different sensors. Context depends on the application domain. That is why the context hierarchy given in Fig. 9 can be extended and adapted for a particular domain.

5.5 Mapping with the Low-Level Vision Layer

The previous subsections have introduced the structure of the proposed visual concept ontology. Any knowledge base resulting from this ontology-driven knowledge acquisition process is for classification purposes. During the classification of a given object, numerical descriptors are computed. To be interpreted as visual concepts, a link must be established between computed numerical descriptors and symbolic visual concepts. The extraction

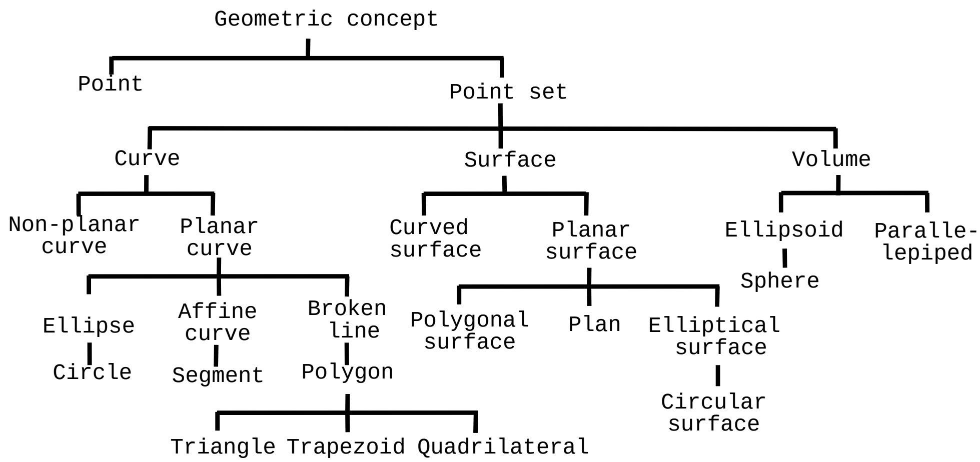

Fig. 6 Geometric concept hierarchy

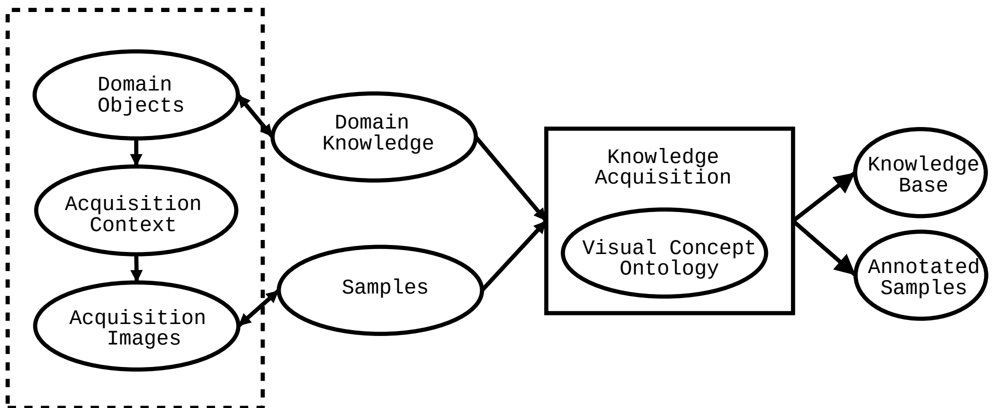

Fig. 8 Contextual knowledge in the global knowledge acquisition process

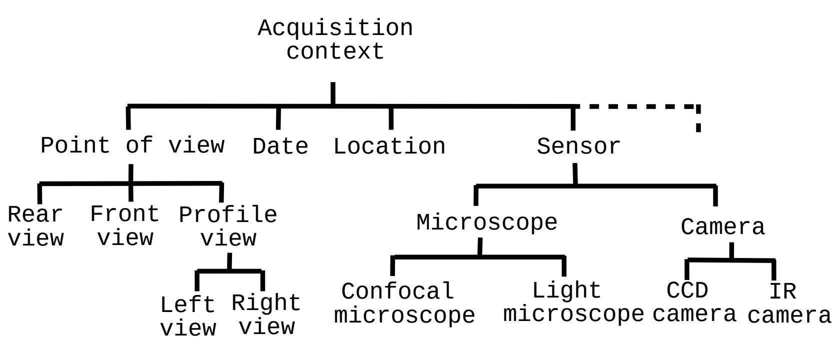

Fig. 9 Context concept hierarchy

of visual concepts from a region of interest is described in Fig. 10.

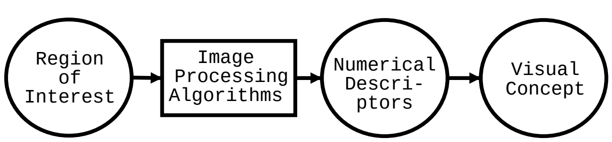

Fig. 10 From a region of interest to a visual concept

Currently the link between symbolic visual concepts and numerical descriptors is manually defined. A set of currently calculated shape descriptors is given in Table 3. Subsets of these descriptors are associated with visual concepts. For example, the ratio $Length/Height$

computed for a region of interest is used to characterize the *Elongation* visual concept. Currently, numerical descriptors associated with the Texture concept are statistical moments and Gabor descriptors (Manjunath et al. 1996). Color characterization is done with histograms and color coherence vectors (Pass et al. 1996).

Visual concept meaning may depend on context. For instance, the notion of elongation depends on the image acquisition point of view. That is why descriptor association is conditioned by the context description process described in the previous subsection.

6 Knowledge Representation

In the previous section, we have obtained a conceptualization for a visual concept ontology. The result of the conceptualization process is an abstract object. Before obtaining an operational entity, a representation formalism has to be chosen. Different kinds of representation formalisms are enumerated in (Crevier et al. 1997). Commonly used techniques are formal logics, fuzzy logics, frames, semantic nets or description logics (Moller et al. 1999).

A domain object is described through four categories of relations :

1. *Spatial Attributes : geometry, size, orientation, position*
2. *Color Attributes : hue, brightness, saturation*
3. *Texture Attributes : repartition, contrast, pattern*
4. *Context Attributes*

We use frame based formalism (which is well adapted to the representation of taxonomical expert knowledge). A complete formalized example is given in table 4.

7 A Knowledge Acquisition Tool for Image Description

7.1 Overview

Section 5 contains details about the structure of a visual concept ontology. To be used as a guide for the description of domain objects, a dedicated graphical tool has been developed. This tool is currently able to carry out three distinct tasks:

1. domain knowledge definition
2. visual concept ontology-driven symbolic description of concepts and their subparts
3. image samples management

The output result of the acquisition process is a knowledge base composed of domain classes described by visual concepts provided by the ontology.

The formalism used to structure the resulting knowledge is a frame based formalism. Java has been used to create this tool.

7.2 Tool Characteristics

Our tool allows domain knowledge creation. As can be seen in Fig. 11 and Fig. 12, domain knowledge is organized as a taxonomy of domain classes in a specialization

Descriptor	Formula
Length (L)	Maximum projection
Width (W)	Maximum orthogonal to length
$Ratio\ \frac{L}{W}$	$\frac{Width}{Length}$
Area (A)	Number of pixels
Form Factor	$\frac{4\pi A}{P^2}$
Perimeter	Perimeter length
Roundness	$\frac{4A}{\pi L^2}$
Equivalent circular diameter (ECD)	$\sqrt{\frac{4A}{\pi}}$
Compactness	$\frac{ECD}{L}$
Box area (BXA)	Bounding rectangle
Box ratio	$\frac{A}{BXA}$
Convex hull area (CHA)	Area of convex hull
Convex hull perimeter (CHP)	Perimeter of convex hull
Solidity (S)	$\frac{A}{CHA}$
Concavity (CCav)	$CHA - A$
Convexity (CVex)	$\frac{CHP}{P}$

Table 3 Examples of numerical shape descriptors used to compute geometric visual concepts

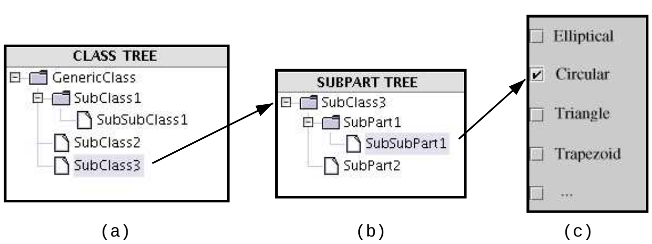

Fig. 11 Description of subpart "SubSubPart1" of class "SubClass3". (a) Domain classes hierarchy (b) Subpart Tree associated with SubClass3 (c) Visual concepts proposed for the description

tree. This approach is natural for people who are familiar with a taxonomic approach (e.g. biologists). Whenever a class is added to the tree, the visual concept ontology is displayed on the screen. The user is then able to describe a new class with the terminology contained in the ontology. As previously explained, a class can be composed of subparts (*subparts* attribute).

Subpart description is performed in the same way as the description of domain classes. Note that the subpart tree is a composition tree and not a specialization tree.

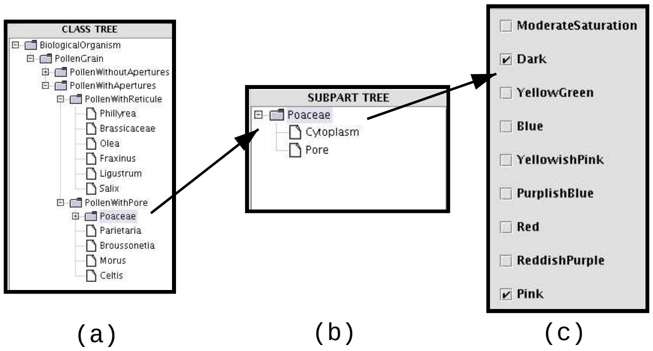

Fig. 12 Description of domain class Poaceae. (a) Domain classes hierarchy (b) Subpart tree associated with domain class Poaceae (c) Color visual concepts used for the description

Every domain class has an associated subpart tree (see Fig. 11).

Another important characteristic of our tool is the sample management module which allows to provide image samples of the visual concepts used during the description phase. First of all, a set of image samples has to be chosen. Then, a region of interest is selected with an interactive drawing called intelligent scissors (Mortensen et al. 1998). Intelligent scissors allow objects within images to be extracted quickly and accurately using simple gesture motions with a mouse. When the gestured mouse position comes in proximity to an edge object, the manually drawn contour is wrapped around the object.

The manually segmented region of interest is used to compute the required numerical descriptors. Fig. 13 describes how a sample of the subpart Pori is provided. Since the Pori subpart is described as being circular, the computation of a form factor on this particular image gives an example of what the notion of circularity is in this particular application domain.

7.3 Results

We propose reusable and extendible methodology for acquiring knowledge related to complex object visual description. The concrete implementation of this methodology currently involves the following elements :

– A visual concept ontology composed of 103 visual concepts and 31 spatial relations.
– 16 numerical descriptors associated with spatial visual concepts. 127 descriptors used to characterize texture concepts (e.g. cooccurence matrices). 512 descriptors (e.g. color coherence vectors) associated with color concepts.
– A knowledge acquisition tool able to guide knowledge base design for knowledge based vision systems

We are currently using these elements in the palynology domain. Automatic pollen grain classification is useful for clinicians so as to provide near real time accurate information on aeroallergens and air quality for sensitive users. Our tool is used as a help for communicating with experts in palynology. This tool is useful for guiding the description of pollen grains in a user-friendly and efficient manner. The visual concepts contained in the ontology can be seen as a communication language between us and the experts. Although sets of numerical descriptors are associated with visual concepts, they are hidden to the expert: when choosing a visual concept, the expert implicitly chooses a set of numerical descrip-

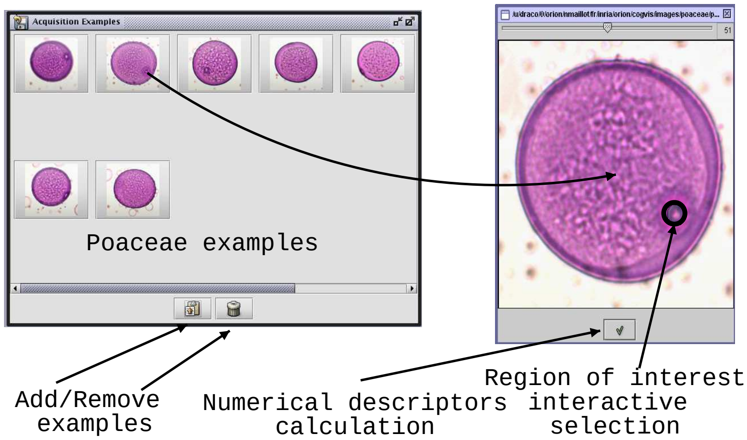

Fig. 13 An example of Poaceae's subpart "Pori" provided by interactive selection of a region of interest

tors. This is why the generated knowledge base is close to low-level vision.

The tool has allowed us to guide the visual description of 30 different types of pollen grains. We have also built a sample database composed 350 images acquired during the A.S.T.H.M.A[1] european project. Table 5 shows how visual concepts are used for describing domain objects. The visual concepts used for pollen grain description have been obtained during a knowledge acquisition process.

8 Conclusion and Future Work

We have proposed an original approach to the creation of knowledge-bases for computer vision systems. The notion of visual concept ontology has been introduced. Its structure is based on three distinct notions: texture, color and spatial concepts. The description is contextualized by a set of context concepts. This ontology can be used as a guide for describing the objects from a specific domain.

[1] http://www-sop.inria.fr/orion/ASTHMA/

Computer vision systems tuned for specific applications rarely take into account domain expertise in an explicit manner. The methodology proposed in this paper is intended to establish a link between the semantic visual description provided by the the experts and the low-level numerical descriptors useful in order to perform object recognition. This link leans on a visual concept ontology composed of visual concepts associated with numerical descriptors.

Another important aspect of the model we propose is the image samples annotated by visual concepts. These samples are currently used to learn visual concept recognition algorithms. For instance, different kinds of texture in the provided image samples allows to learn the difference between a granulated texture and a smooth texture for a given domain. A complete classification system which uses the resulting learned concepts is under development.

Class	*Poaceae*
{	
SuperClass:	*PollenWithPori*
SubParts:	
Pori pori1	[*PoriWithAnulus*]
SpatialAttributes :	
GeometricConcept geometry :	[**CircularSurface EllipticalSurface**]
SizeConcept size :	[**ImportantSize AverageSize SmallSize**]
ColorAttributes :	
HueConcept hue:	[**Pink**]
BrightnessConcept brightness:	[**Dark**]
TextureAttributes :	
TexturePatternConcept pattern:	[**GranulatedTexture**]
TextureContrastConcept contrast:	[**Slight**]
SpatialRelations :	
SpatialRelation r1:	[**NTTP**(*Poaceae,pori1*) **TTP**(*Poaceae,pori1*)]
}	

Table 4 High level description of domain class Poaceae. Visual concepts provided by the ontology are in **bold face**. Attribute names are in SMALL CAPS. Knowledge provided by the expert is in *italic*.

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Expert terminology	Spatial Attribute	Color Attributes	Texture Attributes	Subparts Attributes	superclass
Pollen	**-**	**-**	**-**	**-**	**Expert concept**
Non Apertured Pollen	**-**	**-**	**-**	**-**	*Pollen*
Apertured Pollen	**-**	**-**	**-**	**-**	*Pollen*
Pollen with Pori	**-**	**-**	**-**	**-**	*Apertured Pollen*
Pollen with Colpi	**-**	**-**	**-**	**-**	*Apertured Pollen*
Pollen with Pori and Colpi	**-**	**-**	**-**	**-**	*Aperured Pollen*
Cupressaceae	**Circular Surface and Average Size**	**Brilliant Blue**	**Slightly Granulated**		*Non Apertured Pollen*
Poaceae	**Elliptical or Circular Surface Small or Average or Important Size**	**Dark Pink**	**Granulated Texture**	**-**	*Pollen with Pori*
Parietaria	**Elliptical Surface and Small Size**	**Brilliant**	**Smooth Texture or Granulated Texture**	**-**	*Pollen with pore(s)*
Olea	**Elliptical or Circular Surface Average Size**	**Dark Red**	**Irregular Texture**	**-**	*Pollen with pore(s) and Copli*
Aperture	**-**	**-**	**-**	*Apertured Pollen*	**Subpart**
Pori	**-**	**-**	**-**	*Pollen with Pori or Pollen with Pori and Colpi*	*Aperture*
Colpi	**-**	**-**	**-**	*Pollen with Colpi or Pollen with Pori and Colpi*	*Aperture*
Exine	**-**	**-**	**-**	*Pollen*	**Subpart**
Cytoplasm	**-**	**-**	**-**	*Pollen*	**Subpart**
Pori of Poaceae	**Elliptical Surface**	**Very Light**	**Smooth Texture**	*Poaceae*	*Pori*
Colpi of Olea	**Triangular Surface and Small Size**	**Very Light**	**Smooth Texture**	*Olea*	*Colpi*
Pori of Parietaria	**Elliptical Surface and Small Size**	**Very Light**	**Smooth Texture**	*Parietaria*	*Pori*
Cytoplasm of Cupressaceae	**Polygonal Surface and Important Size**	**Dark**	**Irregular Texture**	*Cupressaceae*	*Cytoplasm*

Table 5 Different types of pollen grains described with visual concepts. Concepts provided by the visual concept ontology are in boldface. Domain knowledge is in italic

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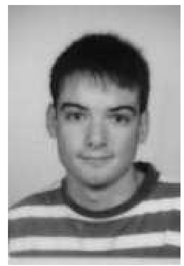

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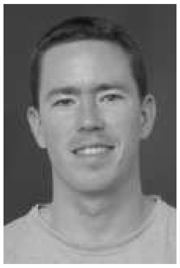

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List of Figures

List of Tables