

University of Liège
Faculty of Engineering



Master Thesis

**A workflow for large-scale computer-aided cytology
and its applications.**

Author : Romain Mormont

Supervisor : Prof. Pierre Geurts

Master thesis submitted for the degree of
MSc in Computer Science and Engineering

Academic year 2015-2016

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Summary

Acknowledgement

Chapter 1

Introduction

Chapter 2

Object detection in large images

2.1 General problem

2.1.1 Formulation

Generic formulation of the object detection problem

2.1.2 Implementation issues

What issues an implementor could face when trying to implement object detection in large images

2.1.3 Related works

What solutions are usually presented in the litterature to solve those problems (shallow overview as this is a wide topic)

2.2 Cytology

2.2.1 An object detection problem ?

Why it is an instance of the "object detection in large images" problem

2.2.2 The thyroid case

Explanation of the Thyroid case

Chapter 3

A generic workflow : Segment Locate Dispatch Classify

3.1 Principle

3.1.1 History and first developments

The Segment-Locate-Dispatch-Classify (SLDC) workflow was first imagined by ?? Jean-Michel Begon ?? as a generalization of the work on thyroid nodule malignancy detection made in [Deb13]. In the context of this master thesis, the author had implemented a processing workflow for detecting cells with inclusion and proliferative patterns (see ?? (thyroid)) in digitized thyroid punctions slides. The cells and patterns were detected by segmenting the images and then classified using machine learning techniques. As explained in the Section ?? (thyroid), the patterns could themselves contain cells with inclusion, so the author implemented a second processing workflow to detect those cells in the patterns. The idea behind the second workflow was similar to the first, that is segmenting the patterns and then classifying the detected objects.

From those workflows, a common pattern emerged : performing detection using a segmentation algorithm and then classifying the detected objects using machine learning techniques. This pattern was at the root of the SLDC workflow idea.

3.1.2 Algorithm : scope, terminology and notations

The workflow is a meta-algorithm¹ that detects and classifies objects contained in images. Particularly, given an image \mathcal{I} as input, it is expected to output the information about the objects of interest in this image. It is worth noting that genericity is of the essence in this case. The algorithm should be usable for solving the widest possible range of object detection and classification problems while keeping minimal the work of the implementor.

Formally, the algorithm can be seen as an operator $\mathcal{SLDC}(\cdot)$ such that

$$\mathcal{SLDC}(\cdot) : \mathcal{I} \rightarrow \{(o_1, C_1), \dots, (o_N, C_N)\} \quad (3.1)$$

where (o_i, C_i) is a tuple of which the first element, o_i , is the information about the i^{th} object of interest found in \mathcal{I} and the second, C_i , its classification label.

In the subsequent sections, some additional operators are defined and used to implement the $\mathcal{SLDC}(\cdot)$ operator. First, a basic version of the algorithm is presented and then

¹In this context, a meta-algorithm is an algorithm that coordinates the execution of other algorithms.

refined in order to achieve an acceptable level of genericity. Finally, the final algorithm is presented.

Additional operators

Segmentation The segmentation is the step where the detection will actually be carried out. Formally, the goal of this phase is transform an image \mathcal{I} into a binary mask \mathcal{B} of which the pixel b_{ij} is 1 if the pixel p_{ij} of \mathcal{I} located in an object of interest. Otherwise, it is set to 0. The segmentation operator $\mathcal{S}(\cdot)$ is such that

$$\mathcal{S}(\cdot) : \mathcal{I} \rightarrow \mathcal{B} \quad (3.2)$$

Classification The classification is performed using a classification model which can be seen as an operator $T(\cdot)$ such that

$$T(\cdot) : o \rightarrow \mathcal{C} \quad (3.3)$$

where o is an object and \mathcal{C} the corresponding classification label.

Location While the segmented image theoretically contains all the information required about the detected objects (i.e. shape and position in the image), the format of this information is inconvenient to query mostly because a single object cannot be extracted easily. The goal of the location step is therefore to transform the information into more convenient format which encodes both the shape of the object and its position in the image. A mathematical object which matches this specification is a polygon and was chosen as representation. The location operator $\mathcal{L}(\cdot)$ can be seen as

$$\mathcal{L}(\cdot) : \mathcal{B} \rightarrow \{P_1, \dots, P_N\} \quad (3.4)$$

where \mathcal{B} is a binary image generated by a segmentation operator as defined in 3.2, N is the number of object of interest in \mathcal{B} and P_i is the polygon generated for encoding the shape and position information of the i^{th} object in the image.

Single segmentation, single classification model

The most basic way of implementing the \mathcal{SLDC} operator is to

As suggested by the pattern introduced in Section , the workflow detects the objects using a segmentation algorithm and classifies the objects using a classification models. For the sake of genericity, those components, which are usually highly problem-dependent in image processing, are provided by the implementor and the workflow coordinates their execution to produce the desired output. That is why the workflow is called a *meta-algorithm* as it actually coordinates other algorithms.

As genericity is of the essence in this context, the

The workflow is an object detection and classification algorithm. Therefore, it takes as input an image and outputs a set of objects of interest found in this image. Especially, the algorithm is expected to return information about the shape and location of those objects. In addition to those information, a classification label is computed using a classifier and associated with every object. Due to the possible variability of the elements to detect in the images, the workflow can use different classifiers to predict the target label. Therefore, before being classified, an object is first dispatched to one of these classifiers.

Formalization

As suggested by its name, the workflow is composed of four steps.

Segment The first step consists in finding objects of interest in the input image, that is, finding grouping of pixels composing those objects. This step can be formulated as a segmentation problem where each pixel is associated a binary value indicating whether it belongs or not to an object of interest. Given the input image \mathcal{I} , this step therefore produces a binary image \mathcal{B} of which the pixel b_{ij} is set to 1 if the pixel p_{ij} of \mathcal{I} is located in an object of interest. Otherwise, b_{ij} is set to 0. Formally, we have a segmentation operator $\mathcal{S}(\cdot)$:

$$\mathcal{S}(\cdot) : \mathcal{I} \rightarrow \mathcal{B}$$

Locate The second step consists in extracting the information about the shape and location of the objects of interest from the binary image \mathcal{B} and to convert this information into a convenient format such as a polygon (see Section 3.1.2 for more details about this representation). Given the binary image \mathcal{B} and given that it contains K distinct regions of interest, this step produces K polygons where the polygon P_i represents the geometric contour of the i^{th} object of interest. Formally, we have a location operator $\mathcal{L}(\cdot)$:

$$\mathcal{L}(\cdot) : \mathcal{B} \rightarrow \{P_i | i \in \{1, \dots, K\}\}$$

Dispatch At this step, the workflow must dispatch each polygon to its corresponding classifier. To achieve this goal, it uses a the

Classify

On encoding location and format using a polygon

Chaining workflows

3.1.3 Framework

Describe what we expect from a framework implementing the workflow (parallism, easy to use,...)

3.2 Implementation

3.2.1 Technologies

Describe and justify the choice of Python and of the various dependencies

3.2.2 Software architecture

Detail of the software architecture

3.2.3 How to use the framework

A toy example : finding disks in an image with grey background and guessing whether they're black or white

Chapter 4

SLDC at work : the thyroid case

4.1 Cytomine

Presentation of cytomine

4.2 Implementation issues

Presentation of implementation issues related to the thyroid case (image size, over HTTP, image quality, human annotation vs computer annotation, presence of inclusions in patterns, dispatching ...)

4.3 Implementation

Actual implementation of the processing using the workflow

4.4 Performance analysis

4.4.1 Detection

4.4.2 Execution time

Chapter 5

Conclusion

Notations

Image :

\mathcal{I}	An image
w	The width of an image
h	The height of an image
c	The number of channels of an image
\mathcal{I}_{hw}	An two dimensional image of width w and height h
p_{ij}	A pixel at row i and column j of a two dimensional image
\mathcal{B}	A binary image
$b_{ij} \in \{0, 1\}$	A pixel of a binary image
P	A polygon

Machine learning :

$T(\cdot)$	A classifier
C	A classification label

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Bibliography

- [Deb13] Antoine Deblire. “Segmentation et classification automatiques de cytoponctions de la thyroïde.” fr. MA thesis. Université de Liège, Liège, Belgique, 2013, p. 74.