Tremplin recherche ESIEE – 2021/2022

Digital Topology for Anatomical Modeling in Medical Imagery

Hosting laboratory
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International partner
Medical Image Analysis Lab. – Tokyo University of Agriculture and Technology (TUAT), Japan

Targeted ESIEE departments
Computer science, Datascience and artificial intelligence, Biotechnologies - e-health

Hosting team
This project will be in the framework of the research collaboration between LIGM, supported by CNRS and Université Gustave Eiffel, in France and Medical Image Analysis Lab of TUAT in Japan.

Context
In medicine, advances in image capture devices allow us to gather information about human internal structures in a noninvasive fashion nowadays. One of challenges in the field of medical imagery is to investigate and model variability of anatomical shapes and positions of organs mathematically and statistically from those collected images. This research subject, called computational anatomy [1, 2], is one of the main research topic of the Japanese partner. In order to achieve this goal, both theoretical studies and developments of efficient computational tools for image analyses are required. Thanks to the increased access to data, machine learning, deep learning in particular, recently produces competitive results in medical applications [3]. In this project, we also aims at computational anatomy based on deep learning, with focusing on aspects of digital topology, which is one of the specialities of the French partner.

Topology is concerned with the properties of geometric objects that are preserved under continuous deformations without tearing or gluing. There are several topological invariants in three dimensions, such as the number of connected components, cavities and tunnels (see examples for 2D topological invariants in Fig. 1). They are useful to set a strong global constraint for modeling complex anatomical structures. However, topological defects can be frequently observed in practice due to the discontinuities induced by the digitization process of a function defined on a discrete domain, representing a digital image. One possible way to solve this problem would be integrating

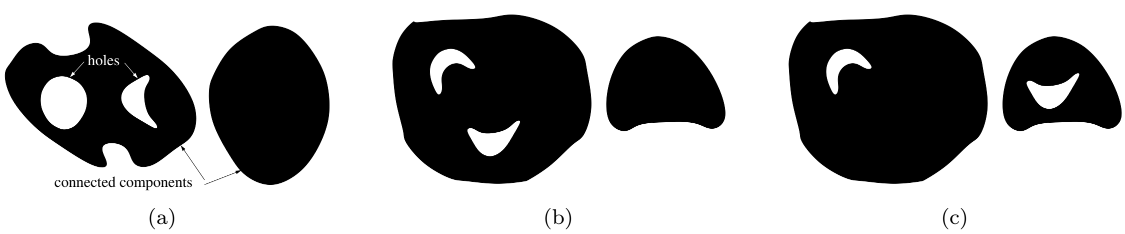
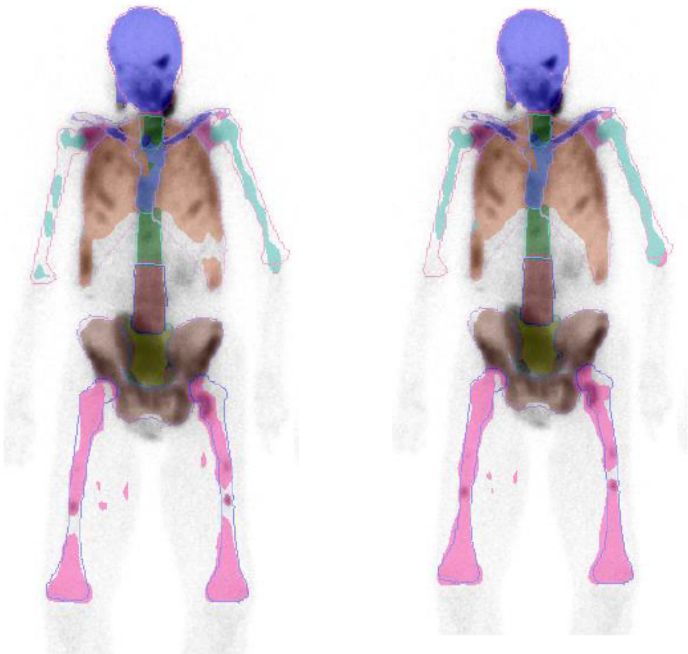


Figure 1 – Illustration of 2D topological invariants. (a,b,c) are all objects with 2 connected components and 2 holes ; (b) can be obtained from (a) by a continuous deformation whereas (c) cannot.



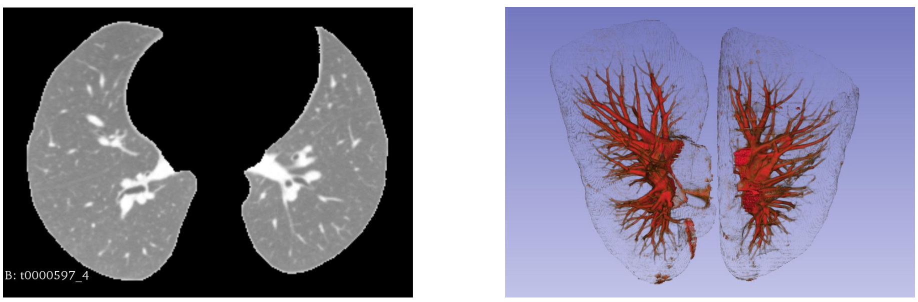
(a) (b)

FIGURE 2 – Segmentation of bones (a) without and (b) with topological constraints

topological loss functions [4] in the learning process by using the differentiability of persistent homology [5], with help of digital geometry and topology [6, 7, 8] and mathematical morphology [9]. See Fig. 2 for a comparison of bone segmentation results with and without topological constraint in this framework.

Goal and challenges

In this project we aim at computational modeling of lung vessels from a set of computed tomography scan images in particular. As mentioned above, one of the popular methods, which recently can produce competitive results in medical applications, is deep learning. However, there are still less study on topological aspects that should be explicitly treated in the learning process. We challenge this problem, which is specific to the lung vessel CT images, such that they globally have tree structures with tube-like local shapes without hole nor cavity (see Fig. 3). With such prior topological knowledge, our goal is to propose a new method of computational modeling of lung vessels with geometrical and topological consistency, based on deep learning.



(a) (b)

FIGURE 3 – (a) A cross section of a 3D CT pulmonary scan (pulmonary regions are extracted) and (b) segmented pulmonary vessels

Skills desired and/or developed during the project

Image analysis – programming – machine learning (deep learning) – digital topology

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