Combining Medical Image Analysis and Process Modelling

In combination of medical image analysis and process modelling, we can observe how medical image computing is growing in significance in terms of medical diagnostics and image-guided therapy. Recently, image analysis systems are seen at use to integrate advanced image computing methods and are used in practice for the extraction of quantitative image parameters or supporting the surgeon during a navigated intervention.

Using process modelling, we can see enabled improvements of image analysis algorithms in terms of automation, accuracy, reproducibility and robustness. In addition, we can expect model-based image computing techniques to open up new perspectives for prediction of organ changes and risk analysis of patients. Complex models are used in different medical applications and medical images like radiographic images, dual-energy CT images, MR images, diffusion tensor images, as well as microscopic images. Thus, given these implementations, we can observe the high potential and range of modelling applied to medical images.

Business process modelling and notation (BPMN) is a graphical representation of a company's business processes or workflows, as a means of identifying potential improvements. The focus is on discovering, designing, deploying, interacting with, operating, optimizing and analyzing end to end processes. Interesting examples of BPMN implementation involve modelling anatomic pathology processes in a public hospital in Spain.

Convolutional neural networks are used for efficiency improvement in radiology practices through protocol determination based on short-text classification. In addition, applications may include reduction of gadolinium dose in contrast-enhanced brain MRI by an order of magnitude without significant reduction in image quality. Applications of deep learning in radiotherapy, PET-MRI attenuation correction, radiomics, and theranostics in neurosurgical imaging to combine confocal laser endomicroscopy with deep learning models for automatic detection of intraoperative CLE images on-the-fly, are to be observed.

Technical and Medical Challenges

Some of the issues that may arise in image analysis is the validation of segmentation methods For some scientists, the image data and reference is usually not available and it is impossible to reproduce the conclusions.

Large data volumes are a huge issue. These may include medical image management and image data mining, bioimaging, virtual reality medical visualizations and neuroimaging. Given the increasing amount of data, image processing and visualization algorithms need adjustment. The solution to this lies in scalable algorithms and advanced parallelization techniques using GPUs.

Three main challenges in medical image processing begin with the need for access to large high-quality labelled datasets for training. A possible fictitious solution may involve augmentation. Augmentation is used by scientists to double, triple or even quadruple datasets, by modification of the available images so that new images are created which still shows the same characteristics, but slightly different and seen as training material by the neural network.

The next challenge is that the most successful deep learning models are currently trained on simple 2D pictures. CT-and MRI-images are usually 3D, adding literally an extra dimension to the problems. Thus, conventional x-ray images may be 2D, where current deep learning models are not adjusted to these either. Thus, in order to solve this problem, we must gain more experience with the application of neural networks to 3D medical images.

Lastly, due to non-standardized acquisition of medical images, we face one of the biggest challenges. The more variety inside the data, the larger the dataset needs to be to ensure the deep learning network results in a robust algorithm. A solution for solving this problem lies in application of transfer learning, a pre-processing technique applied to overcome scanner and acquisition specifics.

Overall, deep learning will play a major factor in the reality of medical image analysis, as companies begin to apply it for production (via process modelling). We must see the sizes of medical image datasets increase by aggregation (clustering) or augmentation, gain experience with 3D images, and have the medical community standardize medical acquisition for real progress.

Ethical Issues of AI, Process Modelling and Medical Image Analysis

Adoption of AI practices to process medical images for classification will face ethical concerns. Challenges may include addressing how databases and algorithms may introduce bias into the diagnostic process and that AI may not perform as intended. This can lead to a potential for patient harm. In this case, major implications are seen in how clinical laboratories and anatomic pathology groups may use artificial intelligence. Thus, medical laboratory executives and pathologists should be aware of possible drawbacks to the use of AI and machine-learning algorithms within the diagnostic process.

A problem that may arise may occur in implementing machine-learning algorithms that have different interests such as the fact that different treatment decisions about patients are made depending on insurance status or inability to pay.

In light of process modelling, the issue lies within the uncertain nature of processing models. In addition, there lies an absence of accountability and ownership for the management of ethical risks.

In terms of medical image analysis, it may be helpful to include datasets of patients of the age 18 or older. Another ethical issue lies in the need for consent for the use case of patient images. In addition, anonymization of image datasets was involved to remove items from DICOM headers. To ensure correct and only scientific usage of data, benchmark participants have to sign an end-user agreement. An example of safe storage in the cloud is found in implementation of VISCERAL Benchmarks running on Microsoft (Azure), where only authorized participants who signed the end-user agreement has access to stored data.
Lastly, long-term usage of data may involve an additional amendment to allow BRATS dataset for computer-based segmentation of brain lesions be maintained by VISCERAL.

Furthermore, acquiring medical imaging research data is not an easy process. Data privacy needs to be respected and agreed upon by medical ethics commissions of participating institutions. Safe storage and access of data in the cloud may lead to a continual, protected medical data analysis given the risks of data misuse can be reduced in a straightforward way.