Editorial

Radiomics

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In the field of medicine, radiomics is a method that extracts large amount of features from radiographic medical images using data characterization algorithms.[1-5] These features, termed radiomic features, have the potential to uncover disease characteristics that fail to be appreciated by naked eye.[6] The hypothesis of radiomics is that the distinctive imaging features between disease forms may be useful for predicting prognosis and therapeutic response for various conditions, thus providing valuable information for personalized therapy.[1,7,8]

Radiomics emerged from the medical field of oncology[3,9,10] and is the most advanced in applications within that field. However, the technique can be applied to any medical study where a disease or a condition can be tomographically imaged. The underlying image data that is used to characterize tumor is provided by medical scanning technology. The scans produce raw volume of data which must be further processed to be usable in medical investigations to get actual images that are interpretable; a reconstruction tool must be used.[2] There are a variety of reconstruction algorithms, so consideration must be taken to determine the most suitable one for each case, as the resultant images will differ. This influences the quality and usability of the images which in turn determines how easily an abnormal finding can be detected and how well it can be characterized.

The reconstructed images are saved in a large data base. After the images have been saved in the database, they have to be reduced to the essential parts, in this case the tumors, which are called "volumes of interest".[2] Because of the large data that needs to be processed an automatic and semiautomatic segmentation algorithms are used. An algorithm must score as high as possible in the following four tasks; i.e. it must be reproducible, should have consistency, needs to be accurate and should be time efficient. After the segmentation, many features of the tumors may be computed. They stretch from volume, shape, surface to density and intensity as well as texture, tumor location, relations with the surrounding tissues and lots of others. Due to its massive variety, the data needs to be qualified as well, so that we can eliminate redundant information. Hundreds of different features need to be evaluated so we need feature selection algorithms to accelerate this process. After the selection of features it is crucial to analyze the chosen data, where there are different methods to finally analyze. First the different features are compared to one another to find out whether they have any information in common and to reveal what it means when they all occur at the same time. Another way is supervised or unsupervised analysis. Supervised analysis uses an outcome variable to be able to create prediction models. Unsupervised analysis summarizes the information we have and can be represented graphically so that conclusion of our results is clearly visible.[11]

Several steps are necessary to create an integrated radiomics database. The imaging data which are to be exported must not lose any of its integrity when compressed. The integration of clinical and molecular data is important as well and a large image storage location is needed. The goal of radiomics is to able to use this database for new patients. The means that we need algorithms that run new input data through the database which return a result with information about what the course of the patients' disease might look like. For example how fast the tumor will grow or how good the chances are that the patient survives for a certain time, whether distant metastases are possible and where. This determines how the further treatment (like surgery, chemotherapy, radiotherapy or targeted drugs etc) and the best solution which maximizes survival or improvement is selected. The algorithm has to recognize correlations between the images and the features, so that it is possible to extrapolate from the database material to the input data.[5,8]

Radiomics features can be divided into five groups: size and shape based-features, descriptors of the image intensity histogram, descriptors of the relationships between image voxels, run length matrix, size zone matrix and neighborhood gray tone difference matrix derived textures, textures extracted from filtered images and fractal features. The mathematical definitions of these features are independent of imaging modality and can be found in the literature.[11-14]

Multiparametric radiological imaging is vital for detection, characterization and diagnosis of many different diseases. However current methods in radiomics are limited to using single images for the extraction of these textural features and may limit the applicable scope of radiomics in different clinical settings. Recently, a multiparametric imaging radiomic framework termed MPRAD for extraction of radiomic features from high dimensional datasets was developed 16 and was tested on breast cancer and stroke. In breast cancer, the MPRAD framework classified malignant from benign breast lesions with excellent sensitivity and specificity of 87 % and 80.5 % respectively with an AUC of 0.88.[16] Similarly in stroke MPRAD TSPM entropy exhibited significant difference between infarcted tissue and potential tissue-at-risk. Moreover radiomic features help in predicting risk of distant metastases, assessment of cancer genetics, image guided radiotherapy, distinguishing true progression from radionecrosis and prediction of challenging physiological events such as brain activity.

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