EC NEUROLOGY
Editorial

Topological Features are More Critical than Radiomics Features for Texture Analysis

Vishnu Swarup[1], Yashbir Singh[2], Himanshu Narayan Singh[3]* and Gunnar E Carlsson[4]*

[1]Neurology, All India Institute of Medical Sciences, New Delhi, India

[2]Radiology, Mayoclinic, Rochester, Minnesota, USA

[3]Systems Biology, Columbia University Irving Medical Center, New York, USA

[4]Department of Mathematics, Stanford University, USA

***Corresponding Author:** Gunnar E Carlsson and Himanshu Narayan Singh, Department of Mathematics, Stanford University, and Systems Biology, Columbia University Irving Medical Center, New York, USA.

Received: December 01, 2021; **Published:** December 31, 2021

Radiomics is a technique for extracting quantitative features from medical images and analyzing them to make predictions. For malignancy and survival analysis, genomic expression analysis, cancer progression, and assessment, radiomics is widely used. However, radiomics does not obtain information about connected components, loops, or voids from a region of interest. Although Topological data analysis uses persistent homology to generate multiscale features from an image, we introduce a newer approach here. Topological features, we believe, can be more valuable than radiomics features for texture analysis. Before moving ahead, we provide a small picture of radiomics and Topological data analysis. Advancement in high-throughput computing has aided the development of radiomics, an emerging field in medicine. Radiomics is a strategy to derive quantitative features from the MRI scans for clinical, diagnostic, and predictive analysis. Radiomics features can be categorized into three major groups: shape (e.g., volume, surface area, etc.), intensity (e.g., energy, entropy, etc.), and texture features (e.g., run-length features, gray level co-occurrence matrix,etc.). Texture features, which describe statistical relationships between voxels with distinct contrast values, are frequently used as primary quantitative features in radiomics. Radiomics features were using successfully for analyzing different clinical investigations [1-5]. However, topological data analysis is a relatively new concept in applied mathematics that aims to characterize shapes in massive quantities of data. Persistent homology is the most common method for analyzing topological data, and it has been used in a variety of fields (including chemistry, engineering, astronomy, biology, and medicine) [6-9]. TDA's ability to identify shapes despite certain deformations in space makes it noise-resistant. It leads to the discovery of data properties that are not discernible by traditional data analysis methods. A point cloud is used as the input data for the computation of persistent homology. The primary focus of Topological Data Analysis (TDA) in this area is the development of methods to accelerate the computation of Persistent Homology. The output is a set of real number pairs (birth and death times) that document the spatial resolutions at which each topological feature first appears (birth) and disappears (death) (death). The pairs are usually represented as a set of lines, known as barcodes, points in a 2D plane, a persistence diagram, or a persistent landscape. Informally, persistent homology is a method for topological computing features of a data set (point cloud) at various spatial resolutions. It captures topology evolution with increasing (or decreasing) resolutions, providing a multiscale view of a space's topology.

Radiomics features from medical images have been successfully used to noninvasively analyze various types of cancer and clinical data. Radiomics features, on the other hand, can vary significantly depending on noise and other clinical parameters. there is a need for more powerful and meaningful features that can be used in conjunction with the radiomics features. On the other hand, TDA presents a systematic approach for noninvasively extracting potentially significant topological / geometrical features from data while ensuring stability against noise and metric choice. After reviewing the literature, we believe that topological features would be more beneficial for texture analysis than radiomics features. Combining topological and radiomics features for research will also be interesting. In conclusion, this report proposed a method for demonstrating that topological features are more critical for textural analysis than radiomics features.

Bibliography

1. Liu Y., *et al*. "Radiomic features are associated with EGFR mutation status in lung adenocarcinomas". *Clinical Lung Cancer* 17.5 (2016): 441-448.

2. Ren J., *et al*. "Magnetic resonance imaging based radiomics signature for the preoperative discrimination of stage I-II and III-IV head and neck squamous cell carcinoma". *European Journal of Radiology* 106 (2018): 1-6.

3. Zhang J., *et al*. "A radiomics model for preoperative prediction of brain invasion in meningioma non-invasively based on MRI: a multicentre study". *EBio Medicine* 58 (2020): 102933.

4. D'Antonoli TA., *et al*. "CT radiomics signature of tumor and peritumoral lung parenchyma to predict nonsmall cell lung cancer postsurgical recurrence risk". *Academic Radiology* 27.4 (2020): 497-507.

5. Vallieres M., *et al*. "Radiomics strategies for risk assessment of tumour failure in head-and-neck cancer". *Scientific Reports* 7.1 (2017): 1-14.

6. Lum PY., *et al*. "Extracting insights from the shape of complex data using topology". *Scientific Reports* 3.1 (2013): 1-8.

7. Adams H., *et al*. "Persistence images: A stable vector representation of persistent homology". *J Mach Learn Res.* 18 (2017): 1-35.

8. Zomorodian A and Carlsson G. "Computing persistent homology". *Discrete and Computational Geometry* 33.2 (2005): 249-274.

9. Singh Y., *et al*. "Non-ischemic endocardial scar geometric remodeling toward topological machine learning. Proceedings of the Institution of Mechanical Engineers, Part H". *Journal of Engineering in Medicine* 234.9 (2020): 1029-1035.

Volume 14 Issue 1 January 2022