Cardiac Computer-Aided Diagnosis using Cine-MRI Radiomics

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1. Motivation

Cardiac cine-MRI (Magnetic Resonance Imaging) is expected to play an important role due to its ability to quantify in detail structural and functional properties of the beating heart. However, visual assessment of cardiovascular diseases (CVDs) using cine-MRI remains challenging and labor-intensive due to the complexity of these diseases. In this paper, we propose a radiomics [1] approach in which a large number of imaging descriptors is calculated from delineated images and analyzed to identify changes in cardiac morpho-function and image appearance due to CVDs.

2. Materials

This study was conducted in the context of the MICCAI 2017 challenge on Automated Cardiac Diagnosis (the ACDC challenge [2]). The database consists of 100 cases comprising cine-MRI data, height and weight information, as well as the diastolic and systolic phase instants for each subject. Five subclasses were included, namely (see examples in Fig. 1)
(1) Normal subjects (NOR).
(2) Patients with dilated cardiomyopathy (DCM).
(3) Hypertrophic cardiomyopathy (HCM).
(4) Abnormal right ventricle (RV)
(5) Myocardial infarction (MINF).

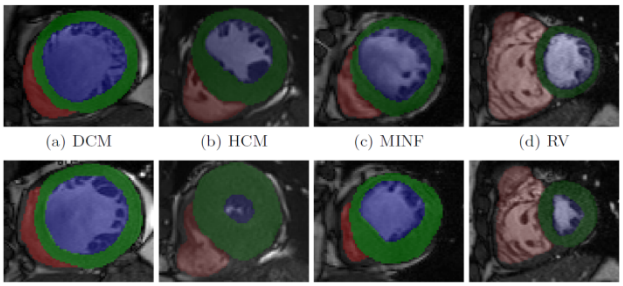

Fig.1 Examples of cine-MRI images for the four abnormalities (Top: ED, bottom: ES)

3. Method

We propose to estimate a large pool (567 features) of complex shape/motion radiomic features, as well as advanced textural radiomic features. In the analysis, we include height, weight, ED-ES duration, plus 188 features per structure: LV, MYO, RV at ED and ES based on five categories, namely:
1) Shape based (Volume, surface area, sphericity, compactness, diameters, elongation, etc).
2) Intensity first order statistics (e.g. mean, standard deviation, energy, entropy, etc).
3) Gray level co-occurrence matrix (GLCM) (contrast, homogeneity, inverse difference moment, etc).
4) Gray level run length matrix (GLRLM) (short/long run emphasis, gray-level/run-length non-uniformity, etc).
5) Gray level size zone matrix (GLSZM) (small/large area emphasis, zone percentage, etc).

The next step is to combine the heterogeneous radiomic features within a classification scheme that will learn to discriminate between the different patient subgroups and normal individuals. In this paper, we use Support Vector Machines (SVMs) due to well-known performance when classifying image data, in particular in the case of small sample size. Furthermore, we use sequential forward feature selection to identify a smaller subset of radiomic features that is optimal for the CVD diagnosis task and to prevent model over-fitting.

4. Results

The forward feature selection results are provided in Fig. 2. where it can be seen than the best single feature only achieves a 0.62 accuracy.

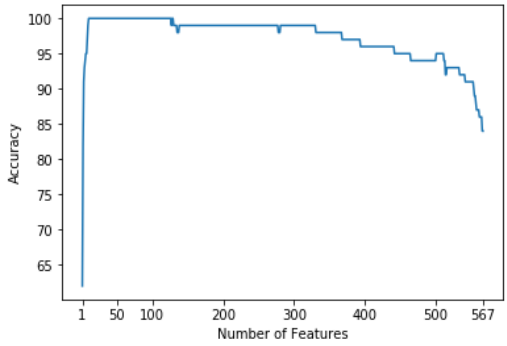

Fig.2 Accuracy of the proposed CVD classification as a function of the number of radiomic features trained in the model.

When combining 10 radiomic features, we reach the maximum accuracy of 1.0. The best features are given in Table 1, which include one conventional shape index (volume), seven advanced shape radiomic features, one patient information (height) and one textural radiomic feature.

Table.1 List of 10 selected radiomic features as selected by the proposed technique for CVD classification. W/O: Accuracy without the feature. Alone: Accuracy using only this feature.

Name	Type	Frame	Structure	W/O	Alone
Volume	Conventional shape	ED	MYO	0.92	0.5
Surface Area to Volume	Advanced shape	ES	LV	0.88	0.62
Least Axis	Advanced shape	ES	LV	0.95	0.42
Maximum 2D diameter	Advanced shape	ED	LV	0.95	0.41
Maximum 3D diameter	Advanced shape	ES	RV	0.97	0.36
GLCM Inverse Difference	Intensity/textural	ES	RV	0.96	0.34
Compactness 2	Advanced shape	ES	LV	0.91	0.40
Maximum 3D diameter	Advanced shape	ES	MYO	0.96	0.47
Surface area	Advanced shape	ED	RV	0.97	0.29
Height	Patient Information	-	-	0.91	0.18

5. Discussion

In this work, we proposed the use of large amounts of radiomic features to predict cardiac subgroups. The obtained results based on MICCAI challenge data suggest that radiomics are indeed capable to encode alterations in the anatomy and tissues of the affected cardiac structures. The feature selection results indicate that shape and intensity descriptors compliment each other and their combinations enable to enhance the prediction power of the system. However, the high accuracy suggests that further evaluations are required to test this model in larger and more variable data samples. Future work also includes the testing of additional radiomic features (*e.g.* fractals, wavelets) and clinical interpretation of the features and results.

References

[1] Cetin, I., Sanroma G., Petersen S. E., Napel S. Camara O., Gonzalez Ballester M.-A., Lekadir K., "A radiomics-approach to computer-aided diagnosis with cine-MRI," in Statistical Atlases and Computational Models of the Heart, 2017.

[2] https://www.creatis.insa-lyon.fr/Challenge/acdc/