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Visual recognition of cardiac pathology based on 3D parametric model reconstruction

Key words: 3D visual knowledge; 3D parametric model; Cardiac pathology diagnosis; Data augmentation

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Motivation

1. Due to the limited availability of annotated datasets, traditional methods usually extract features directly from two dimensional slices of three-dimensional (3D) heart images, followed by pathological classification. This process may not ensure the overall anatomical consistency in 3D heart. Visual recognition of cardiac pathology based on 3D parametric model reconstruction may be able to solve the above problems.

2. Cardiac 3D analysis is essential for the assessment of global and local structural function of the heart. Shape reconstruction is a bridge between computer vision and computer graphics. The concept of visual knowledge, consisting of the prototype and category, can be used to augment cardiac data and improve the performance of cardiac pathology classification.

Main idea

1. In visual knowledge representation of the heart, the average model of different pathological hearts is the prototype, and its category can be determined by principal components with different weight coefficients of 3D statistical shape models (SSMs).

2. The 3D model contains the geometric adjacency information of different sub-structures and 3D morphological structure of the heart, and the clinical indicators obtained via the model are a better approximation of the real heart volumetric information than those using the 2D slices.

3. The cardiac data generated under the constraints of the cardiac visual proposition belongs to the same category of the heart and can be regarded as completely new cardiac data.

Method

1. A 3D model is reconstructed from each set of labeled 2D images representing different pathologies.

2. Based on these reconstructed 3D models, an SSM is employed to construct the 3D parametric heart models. The prototype of 3D parametric models is the mean of SSM. The bases of the category are obtained by PCA. The category is determined via parameter variation of principal components with visual knowledge constraints.

3. The augmentation of heart data can be achieved by random sampling in the category.

4. Shape and motion features of 3D heart models across the two phases are extracted to classify cardiac pathology.

Method (Cont'd)

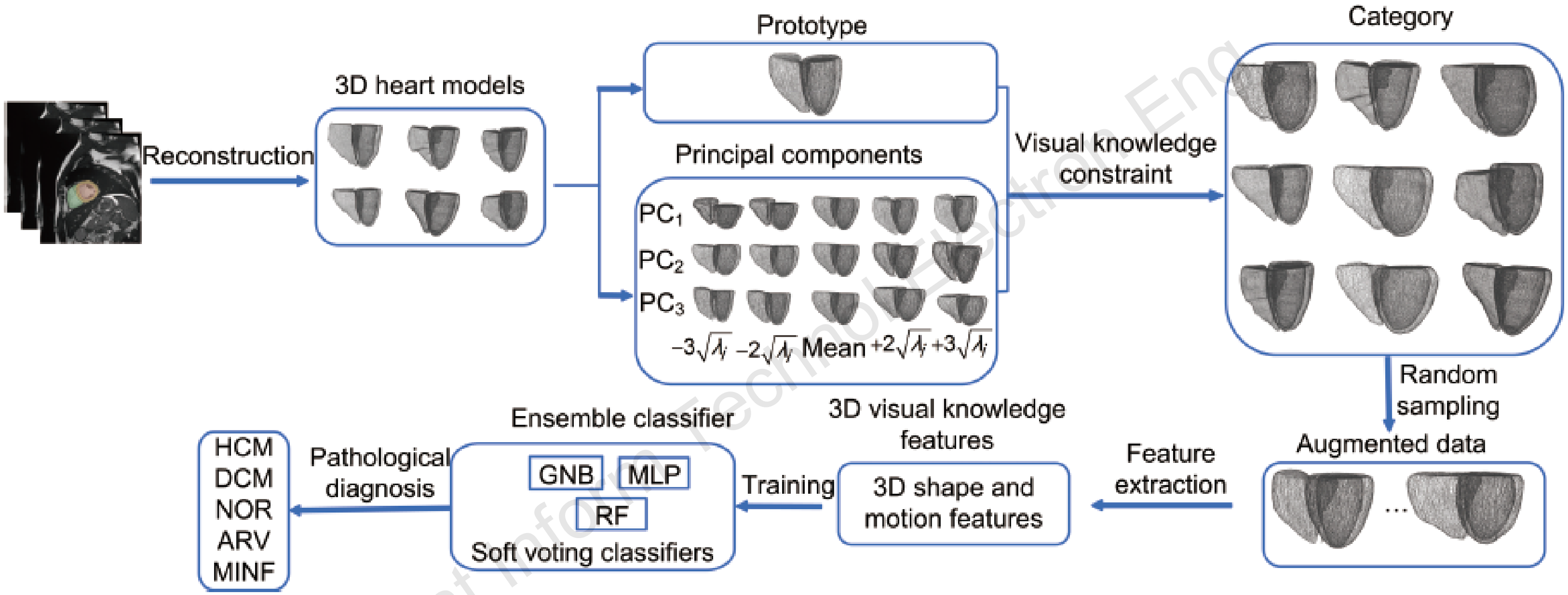

Fig. 1 Overall flow of our proposed algorithm

GNB: Gauss naive Bayes; MLP: multilayer perceptron; RF: random forest; HCM: hypertrophic cardiomyopathy; DCM: dilated cardiomyopathy; NOR: normal; ARV: abnormal right ventricle; MINF: previous myocardial infarction

Major results

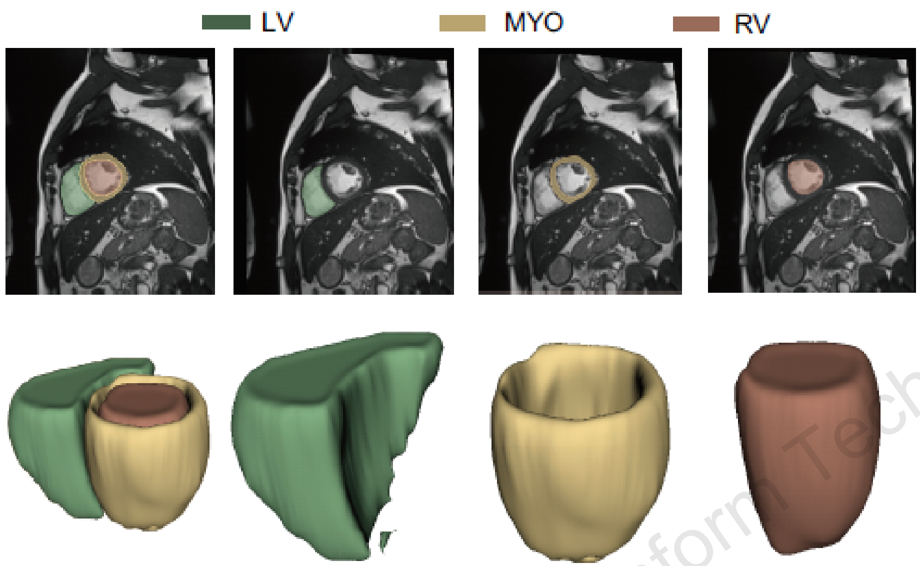

Fig. 2 Schematic of the cardiac tissue and structures as shown in the MRI data

Top row shows the image slices with regions of interest highlighted, and the bottom row shows the reconstructed three-dimensional models of the highlighted structures in the corresponding MRI slices in the top row. LV: left ventricle; MYO: myocardium; RV: right ventricle; MRI: magnetic resonance imaging

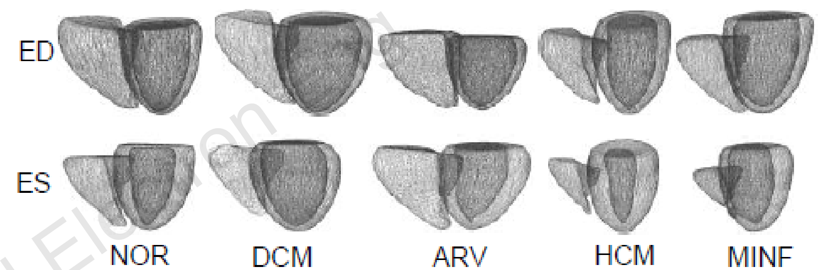

Fig. 4 Prototype demonstration of normal hearts and different pathologies

Top row shows the hearts in the end-diastole (ED) phase, and the bottom row shows the hearts in the end-systole (ES) phase. NOR: normal; DCM: dilated cardiomyopathy; ARV: abnormal right ventricle; HCM: hypertrophic cardiomyopathy; MINF: previous myocardial infarction

Major results (Cont’d)

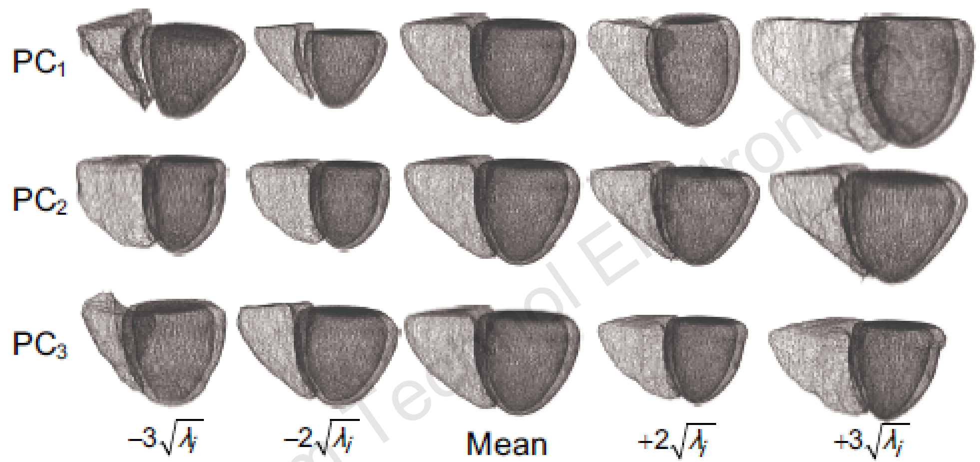

Fig. 6 Prototype of the DCM pathology and instances of the DCM category

The prototype of the dilated cardiomyopathy (DCM) is generated using 18 aligned 3D DCM models. The instance is generated by changing a single shape parameter component (b_{ij}) and fixing all the other parameters at a zero standard deviation from the prototype. The model consists of 4402 left ventricular nodes, 6968 myocardial nodes, and 2787 right ventricular nodes

Major results (Cont'd)

Table 2 Seven types of conventional image based features

Feature	LV	RV	MYO
Volume at ED	√	√	√
Volume at ES	√	√	√
EF	√	√	
ES[vol(LV)/vol(RV)]	√	√	
ED[vol(LV)/vol(RV)]	√	√	
ED[vol(MYO)/vol(LV)]	√		√
ES[vol(MYO)/vol(LV)]	√		√

ED: end-diastole; ES: end-systole; EF: ejection fraction; LV: left ventricle; RV: right ventricle; MYO: myocardium

Table 3 Four types of 3D visual knowledge features

Feature	LV	RV	MYO
Variance of myocardial wall at ED			√
Variance of myocardial wall at ES			√
Variance of LV at ED and ES			√
Variance of myocardial at ED and ES			√

ED: end-diastole; ES: end-systole; LV: left ventricle; RV: right ventricle; MYO: myocardium

Table 4 Disease classification results using different machine learning classifiers on the ACDC testing set (50 cases)

Method	Accuracy (%)	
	Alone	Combination
GNB	84	**92**
MLP	**88**	86
RF	86	**88**
Ensemble	84	**94**

Alone means conventional image based features alone, and combination means the combination of conventional image based features with 3D visual knowledge features. ACDC: automated cardiac diagnostic challenge; GNB: Gauss naive Bayes; MLP: multilayer perceptron; RF: random forest. Best results are in bold

3D features & image-based features

Major results (Cont’d)

Table 5 Noise z and the corresponding parameter b of a generated dilated cardiomyopathy (DCM)

Dimension	Noise z	b_1	b_2	b_3	b_4	b_5	b_6
1	1.785 553 21	393.3479	509.718	423.1248	362.1643	490.8532	378.251
2	1.583 254 10	198.2308	226.3166	205.2633	209.0502	187.0769	202.1402
3	0.760 217 93	82.101 73	90.598 82	75.765 59	66.888 94	76.771 07	71.243 02
4	0.593 141 97	48.418 12	49.673	49.100 32	51.434 54	54.879 08	45.1232
5	−0.485 891 56	−29.3559	−32.8991	−35.0705	−29.3251	−32.5167	−27.7675
6	−0.022 931 55	−1.321 09	−1.402 52	−1.507 11	−1.167 21	−1.415 05	−1.252 35
7	0.058 637 42	3.155 731	3.408 775	3.622 214	2.670 804	3.323 664	2.699 738

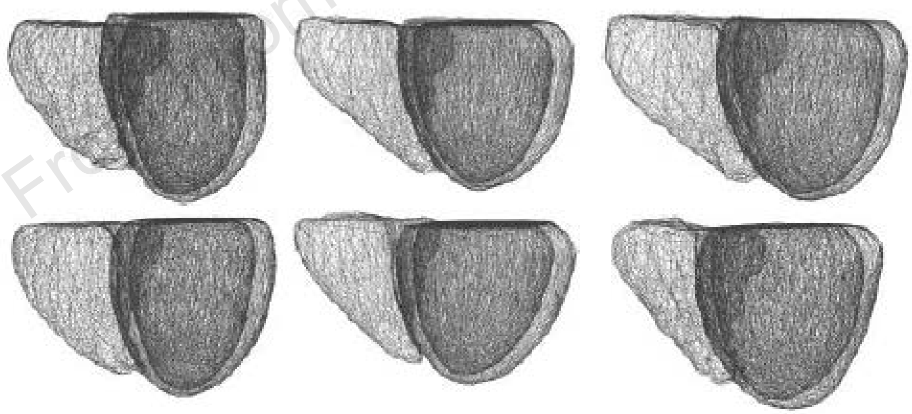

Fig. 8 New dilated cardiomyopathy (DCM) data display with different parameters b

Major results (Cont'd)

Table 6 Classification accuracy of different models on the automated cardiac diagnostic challenge (ACDC) testing set (50 cases)

Method	Accuracy (%)
Isensee et al. (2018)'s	92
Wolterink et al. (2018)'s	86
Cetin et al. (2017)'s	88
Zheng et al. (2019)'s	94
Khened et al. (2018)'s	96
Ammar et al. (2021)'s	92
Chang and Jung (2020)'s	94
Thermos et al. (2021)'s	91
Ours	96

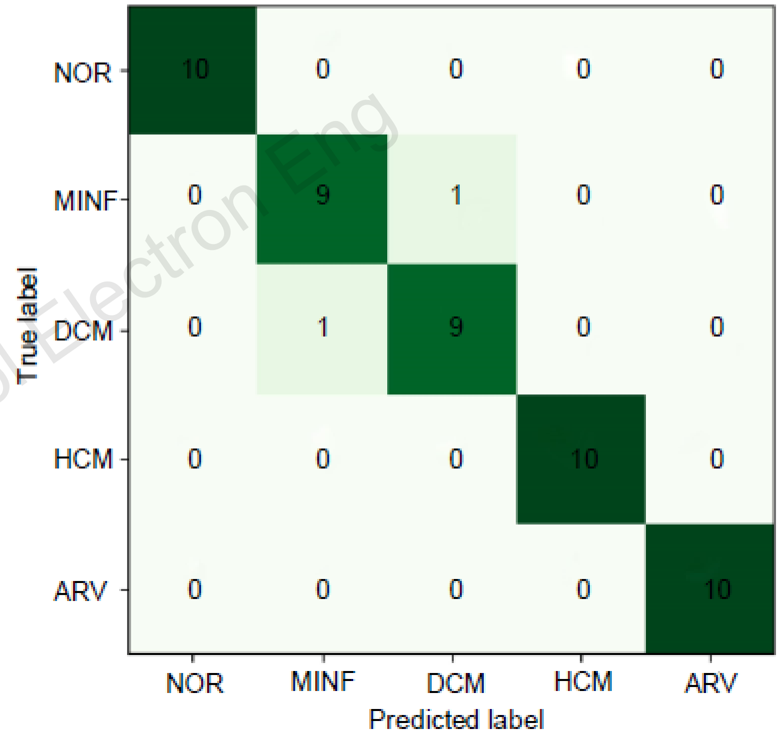

Fig. 9 Confusion matrix of the classification results of the ACDC testing set (50 cases) using the ensemble classifier after adding 20 cases of the DCM data to the training set

Rows correspond to the predicted class and columns correspond to the target class. ACDC: automated cardiac diagnostic challenge; NOR: normal; MINF: previous myocardial infarction; DCM: dilated cardiomyopathy; HCM: hypertrophic cardiomyopathy; ARV: abnormal right ventricle

Conclusions

1. A method for visual recognition of cardiac pathology has been proposed based on 3D parametric model reconstruction, and the results illustrated good performance of the proposed approach on ACDC dataset.

2. Data augmentation based on 3D visual knowledge constraints has achieved especially positive results in the diagnosis of some specific pathologies. This can effectively solve the problem of insufficient samples, and has a good universal applicability in medical image processing.

Yun TIAN is a professor at the School of Artificial Intelligence, Beijing Normal University, Beijing, China. He received his BS degree in computer science and technology from Henan Normal University, in 2003, and his PhD degree in signal and information processing from Northwestern Polytechnic University, China, in 2007. From 2014 to 2016, he served as a postdoctoral fellow at the Joint Research Station of the Chinese Academy of Engineering–Tsinghua University, China. His research interests include medical image processing and pattern recognition.