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Integrating a gradient-based difference operator with machine learning techniques in right heart segmentation

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Abstract. In this research a three step method for right heart segmentation based on a gradient-based difference operator and machine learning techniques is reported. The proposed method is applied to human heart multi-slice computerized tomography (MSCT) volumes. The first step is the preprocessing, where a gradient-based difference operator is applied to exploit the functional relationship between the original input image and its edge enhanced version. In the second step, the least squares support vector machines (LSSVM) are used with a double purpose. First, an appropriate volume-of-interest is automatically established in order to isolate the structure to segment. Second, another LSSVM is trained for locating the voxels required for initializing the seed based clustering procedure. In the third step (segmentation step), the preprocessed volumes are subsequently processed with an unsupervised clustering technique based on simple linkage region growing. Dice score is used as a metric function to compare the segmentations obtained using the proposed method with respect to ground truth volumes traced by a cardiologist. The right atrium, pulmonary valve, right ventricle and venae cavae are segmented from 80 cardiac MSCT volumes. Reported metrics confirm that this method is a promising technique for right heart segmentation.

1. Introduction

Powerful incentives to instigate the researches that generate clinical supports can lead to early diagnosis of diseases and planning of clinical routine procedures useful to raise the quality of life of cardiac patients. The pulmonary hypertension, coronary heart disease, dysplasia and cardiomyopathies are the main cardiac disorders associated with the right side of the heart. In this sense, the evaluation of cardiac structures of the right heart is of great importance in the management of these disorders. However, and despite its important diagnostic value, the assessment of right heart function often remains disregarded in patients referred for cardiac imaging exploration [1].

1.1. The right side of the heart

The right heart is composed by the right atrium (RA), the superior and inferior venae cavae, the tricuspid and pulmonary valves, and the right ventricle (RV). The superior and inferior venae cavae return deoxygenated blood from all peripheral tissues to the right atrium. During the right ventricular diastole,



the venous return flows passively, through the opened tricuspid valve, from the right atrium to the right ventricle. The remaining deoxygenated blood is actively pushed into the right ventricle during atrial systole. During ventricular systole, the right ventricular pressure closes the tricuspid valve, opens the pulmonary valve and then pushes blood into the pulmonary artery.

1.2. Purpose

The objective of this work is to develop an approach for detecting the anatomic structures that conform to the right heart from multi-slice CT sequences. The approach integrates a gradient-based difference operator with machine learning techniques in order to segment the RA, pulmonary valve, RV and superior vena cava. Three-dimensional (3-D) cardiac images are preprocessed using an image-enhancement scheme based on a gradient-based difference operator in order to minimize the artifacts impact in the image sequences and improve the information inside the cardiac structures. Therefore, this enhancement scheme allows to increase the low contrast associated with MSCT sequences. A volume-of-interest (VOI) for each structure is obtained by means of the LSSVM by detecting several anatomical landmarks that allow to locate certain planes useful for isolating the cardiac structure to be segmented. Additionally, a voxel called initial seed is automatically located in each structure of interest using the LSSVM. For each structure of the right heart, the voxel seed is compared with certain neighborhood voxels characteristics such as intensity and topological relationship according to a simple linkage region-growing algorithm.

The segmentation algorithm allows to obtain a binary 3-D image with each structure and the background. In order to validate the accuracy of the structures segmented and assess the performance of the proposed method, the inter and intra-subject variability of the complete approach is evaluated using the Dice score (Ds). The images segmented using the current approach are compared with respect to segmentation manually traced by a cardiologist in the same images.

1.3. Related works

This section is dedicated to presenting previous studies that have some connection with this research. Zhuang et al. [2], propose an automatic method based on the locally affine registration method and free-form deformations with adaptive control point status for segmenting the heart in magnetic resonance imaging (MR). The authors report an average Ds of 0.84, for right ventricle segmentation.

An automatic method based on multi-atlas approach is developed for detecting the outer surface of the pericardium and cardiac chambers in CT images [3]. They report optimal Ds for left ventricle segmentation of 0.91 and the RV of 0.88.

Ghesu et al. [4] propose a pipeline for detecting and for segmenting objects in the context of volumetric image parsing. The problem is solved as a two-step learning problem: anatomical pose estimation and boundary delineation. A learning framework known as Marginal Space Deep Learning (MSDL) is introduced in order to exploit the strengths of efficient object parameterization in hierarchical marginal spaces and the automated feature design of Deep Learning network architectures. Finally, other authors use finite element method [5], level set method [6] and commercially available software [7] in order to automatically segment anatomical structures of the right heart.

2. Materials and methods

An overview of the proposed method is shown on the flowchart in Figure 1.

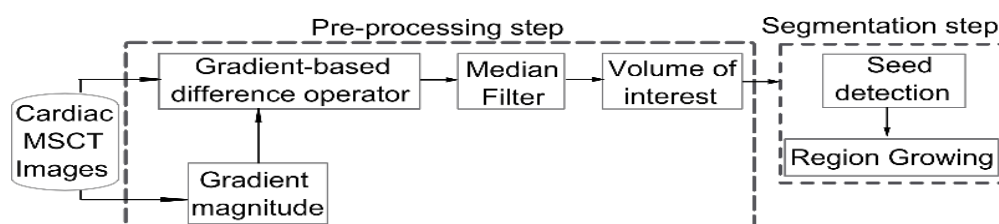


Figure 1. Overview of the proposed right heart segmentation method.

2.1. Data source

The images of this research are derived by two multi-slice computed tomography (MSCT) machines with retrospective electrocardiographic (ECG) gating. Two 64-channel scanners, the LightSpeed VCT and the Discovery CT750 HD General Electric Medical System are used. Each study consists of 20 volumes taken at different times during the ECG-gated cardiac cycle and belongs to a single subject.

Four volumes are captured in signed 12-bits DICOM format. Each volume could contain between 148 and 326 slices. The slice thickness varies from 0.400mm to 0.625mm . In all volumes, the slices have an isotropic resolution of 512×512 pixels, but the pixel size varies from 0.273mm to 0.488mm .

2.1.1. Dataset of points patterns. The dataset of point patterns is constructed from a subset of several volumes of the test dataset which have been enhanced and down sampled. The considered volumes are enhanced using the technique described in section 2.2. A cubic interpolation method is used with the basic idea of reducing the spatial resolution of each volume [8]. The expected reduction factor is 8. In this sense, the slices in the enhancement MSCT volume with a resolution of 512×512 pixels after the down sampling will have 64×64 pixels. A manual process performed by a specialist is applied to locate a circular neighbourhood with radius 10 pixels corresponding to each point. Five points are considered in order to define this dataset. Table 1 and Figure 2 describe the points location.

Table 1. Location of the points for planes construction.

Point	Location
p1	Right atrium–right ventricle joint
p2	Right ventricle apex
p3	Right atrium–superior vena cava joint
p4	Pulmonary valve–pulmonary artery joint
p5	Pulmonary valve–right ventricle joint

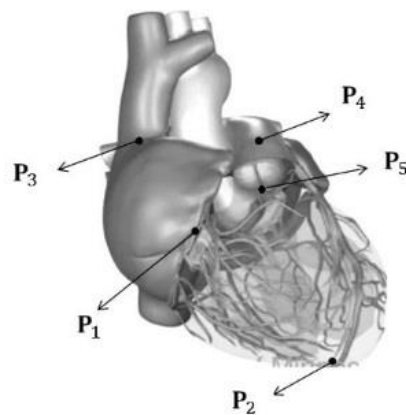


Figure. 2. Location of the points on the right side of heart.

2.2. The gradient-based difference operator

The boundaries between the nearby structures of the right heart are nearly indistinguishable basically by the low contrast to noise ratio of the MSCT images. In this regard, the gradient-based difference operator is proposed as a preprocessing stage for enhancing the computerized tomography volumes and thus improving the generally low contrast of these images.

The operator is defined as the magnitude of difference between the original 3-D image information and the information obtained applying to original image a simple edge detector based on gradient magnitude. For an original image denoted by I_o and its edge enhanced versions I_g , the gradient-based difference operator of the original image denoted by $Og[I_o]$ is computed according to Equation (1).

$$Og[I_o] = |I_o - I_g| \quad (1)$$

2.3. Volume-of-interest definition

Four cropping planes are constructed in order to define the three-dimensional regions on the enhanced image volumes that contain the right heart structures to be segmented. The idea is to isolate the right ventricle of the right atrium, the pulmonary valve of the right ventricle and the pulmonary artery, and finally, the superior venae cavae (SVC) of the right atrium. The construction of each plane requires at least two points located in the MSCT enhanced volume (one of the points belongs to the plane and the vector defined by both points is the normal). The points in Table 1 are considered for this purpose.

2.3.1. Points detection based on supervised learning. The automatic detection of points (p1, p2, p3, p4 and p5) is performed by applying an automatic learning approach. This approach considers a down sampling of the enhanced MSCT volumes followed by the application of a least square support vector machine (LSSVM) [9]. The cubic interpolation method considered to construct the dataset of point patterns (section 2.2) is here also considered as down sampling procedure. The classifiers based on the highly selective LSSVM are implemented in order to identify only those regions that have a high degree of correlation with the training point pattern. A detailed description for the implementation of selective LSSVM, for construction of cropping planes can be found in [11].

The LSSVM classifiers are based on a radial base (Gaussian) kernel function (RBF) with hyper-parameters σ and γ [10]. These hyper-parameters represent the error penalty factor of the learning paradigms and the selectivity factor associated with the width of the RBF kernel, respectively. Five LSSVMs are created to recognize the points needed to build the tricuspid, cava, artery and pulmonary planes.

2.3.2. Seed detection. A process analogous to that developed for the detection of the points that define the cropping planes, is applied for the detection of the seed points using LSSVM. The seeds must be located within the cardiac cavity to be segmented. These seeds are used to initialize the clustering procedure considered in the segmentation step.

2.4. The segmentation procedure

The segmentation step is based on an unsupervised clustering technique that considers the simple-linkage region growing (RG) algorithm in order to group voxels into 3-D regions. This clustering algorithm starts with a seed voxel that lies inside the region of interest ($l \times l \times l$) and grows a region by appending connected neighboring voxels that reaches a certain homogeneity criterion.

The mean (\bar{y}) and standard deviation (σ_s) calculated in the initial region are used to define a range of permissible intensities. This range of permissible intensities constitutes the homogeneity criterion. The voxels that do not fulfill with the homogeneity criterion are rejected. This process is applied to the entire enhancement volume until all voxels are clustered and tagged.

The following steps are used to implement the general procedure of the segmentation stage: 1.) A seed voxel (vs) is taken as the first to analyze. 2.) An initial region is established as a neighborhood of voxels around the seed. 3.) The mean and standard deviation (σ_s) calculated in the initial region are used to define a range of permissible intensities given by $[vs - \tau\sigma_s, vs + \tau\sigma_s]$, where the scalar τ allows to scale the range. 4.) All voxels in the neighborhood are checked for inclusion in the region. In this sense, each voxel is analyzed in order to determine if its gray level value satisfies the condition for inclusion in current region. If the intensity value is in the range of permissible intensities the voxel is added to the region and it is labeled as a foreground voxel. If the gray level value of the voxel is outside the permitted range, it is rejected and marked as a background voxel. 5.) Once all voxels in the neighborhood have been checked, the algorithm goes back to Step 4 to analyze the ($l \times l \times l$) new neighborhood of the next voxel in the image volume. 6.) Steps 4-5 are executed until region growing stops. 7.) The algorithm stops when no more voxels can be added to the foreground region. The method output is a binary three-dimensional image where each foreground voxel is labeled to 1 and the background voxels are labeled with 0. For each of eighty volumes in the test dataset, a binary volume with the right ventricle, right atrium, pulmonary valve and superior vena cava labeled with 1 is obtained.

3. Results

3.1. Setting of the method parameters

The segmentation step is performed for the end-diastolic MSCT volume considering the following:

- The odd size of the neighborhood of the median filter is varied between $3 \times 3 \times 3$ and $9 \times 9 \times 9$.
- In order to set the hyper-parameters of the LSSVM, a fixed and arbitrary value is assigned to σ^2 and values are systematically assigned to hyper-parameter γ . The value of σ^2 is initially set to 25. Then, γ is varied between $[0 \ 100]$ with the step size of 0.25. An analogous process is applied to set the hyper-parameter γ , that is, it is assigned to the optimal value obtained above and, a step size of 0.25 is considered to assign the value range to σ in the interval $[0 \ 50]$. The optimal values of the hyper-parameters are those derived from the above process.
- The region growing algorithm is applied by varying the value of parameters τ and l . In this sense, for τ , all the values included in the interval $[0 \ 10]$ with a step size of 0.1 are evaluated, meanwhile l varies between 1 and 20 with step size of 1.

For each set of parameters the resulting segmented structures are compared with the corresponding structures traced by cardiologists. The differences are estimated using the Dice coefficient as error metric. The metric quantifies the degree of overlap between two volumes and it corresponds to the ratio of twice the volume of intersection to the sum of the two volumes [12].

3.2. Application of the gradient difference operator

The results obtained in the preprocessing step of the three-dimensional MSCT, considering the optimal parameters and the median filtering are presented. The gradient based difference operator is applied to the MSCT volumes, generating an output with a subtle smoothing of the Poisson noise. The smoothing filter based on median filters is then used to minimize this noise effect while preserving the stronger edges. Column b of Figure 3 illustrates the application of the operator to a slice of the MSCT volume. Column c of Figure 3 shows the results of applying the median filter in which the right heart structures are clearly shown.

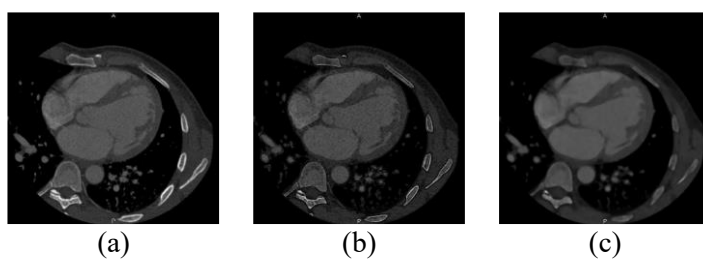


Figure 3. Results obtained for preprocessing step. (a) Original slice, (b) Gradient filter, and (c) Median filter.

3.3. Location of points for planes construction

The process used to define the volume-of-interest generates images in which each right structure to segment is isolated from other structures. Figure 4 shows the obtained isolate region at axial views for each cropping plane.

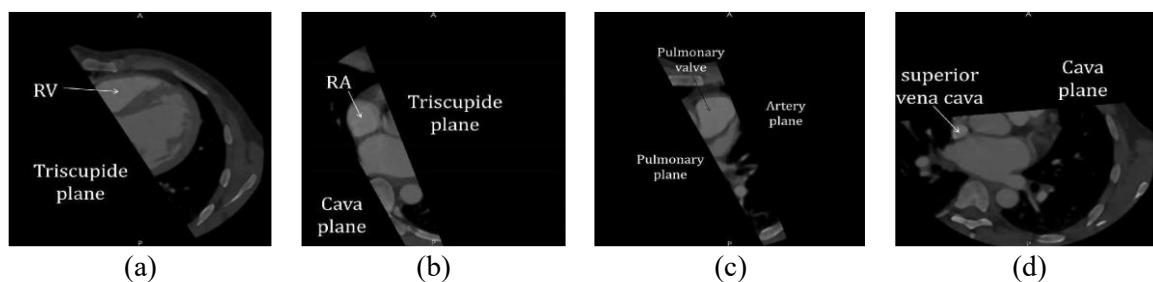


Figure 4. Cropping planes and ROI. (a) RV, (b) RA, (c) PV, and (d) SVC.

3.4. Segmentation of right heart structures

Considering the filtered images at end-diastole time, the RV, RA, PV and SVC are isolated from the other structures using the LSSVM. The size of the median filter kernel is $7 \times 7 \times 7$. The optimal parameters are summarized in Table 2.

Table 2. Optimal parameters for the proposed method.

Parameter	RV	RA	PV	SVC
γ -Hyper-parameter of LSSVM	10	5	2.20	1.75
σ^2 -Hyper-parameter of LSSVM	1.50	2.5	1.38	0.90
l -Neighborhood size for RG	20	3	5	2
τ -Scale factor for RG	3	2.8	3.1	2.8
Maximum D_s	0.9126	0.8300	0.8700	0.9100

For the remaining cardiac instants, the proposed technique is applied, using the optimal parameters obtained considering the image at end-diastole time. In addition, Figures 5, 6, 7 and 8 show ten instants of all segmented structure of one MSCT sequence.



Figure 5. Right ventricle segmentation results.

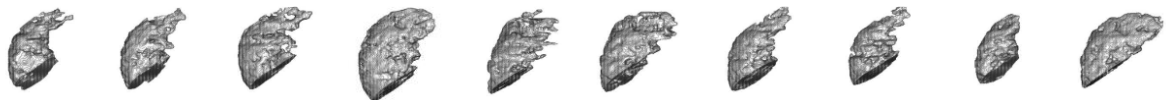


Figure 6. Right atrium segmentation results.

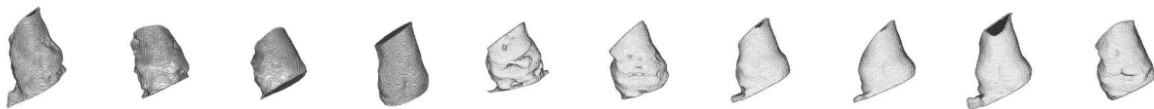


Figure 7. Pulmonary valve segmentation results.



Figure 8. Superior vena cava segmentation results.

Table 3 presents the average values ($\mu \pm \sigma$) for the metric function that quantify the performance of the segmentation three step proposed method. This metric is calculated after segmentation of four databases used for validation. The values in this table are for four structure segmented.

Table 3. Dice coefficient average values for each structure.

	RV	RA	PV	SVC
Dice score	0.8665 ± 0.0471	0.8300 ± 0.0078	0.8700 ± 0.0244	0.9100 ± 0.0061

4. Results discussion

One of the main contributions of the present work is to have segmented the superior vena cava which can be useful in the analysis of its structure to establish if the superior vena cava presents a normal anatomy and functionality or not. Another contribution is generating the 3-D segmentations of both the right ventricle and the right atrium. They are useful to monitor the ventricular and right heart functions.

5. Conclusions

A three step method has been developed based on a gradient-based difference operator and machine learning techniques for segmenting the right heart structures. The segmentations obtained may be useful for the detection of pathologies associated with the right heart size, such as, for example, the detection of hypertensive processes. In addition, this type of segmentation allows the development of computational models that allow the planning of virtual surgical processes related to right heart half.

One of the main contributions of the present work is to have segmented the superior vena cava which can be useful, on the one hand, in the analysis of its structure to establish if the superior vena cava presents a normal anatomy and functionality or not and, on the other, in the construction of realistic models of the superior vena cava using 3-D printers, for therapeutic purposes linked to the planning of radio-chemo therapies processes that allow to minimize the volume or extension of the various neoplasms linked to the superior vena cava syndrome. Another contribution of the present work is to have segmented the pulmonary valve without using multiplanar reconstruction (MPR), which is usually performed in the clinical context before segmenting the 3-D morphology of the valve.

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