

# SEGMENTATION OF TIME SERIES OF CARDIAC COMPUTED TOMOGRAPHY FOR EVALUATION OF THE HEART MECHANICAL FUNCTION

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**Abstract:** In this paper, we propose a segmentation method for time series of 3D cardiac images based on deformable models. The goal of this work is to extend active shape models (ASM) of three-dimensional objects to the problem of 4D (3D + time) cardiac CT image modeling. The segmentation is achieved by constructing a point distribution model (PDM) that encodes the spatio-temporal variability of a training set, i.e., the principal modes of variation of the temporal shapes are computed using some statistical parameters. An active search is used in the segmentation process where an initial approximation of the spatio-temporal shape is given and the gray level information in the neighborhood of the landmarks is analyzed. The starting shape is able to deform so as to better fit the data, but in the range allowed by the point distribution model. Several time series consisting of eleven 3D images of cardiac CT are employed for the method validation. Results are compared with manual segmentation made by an expert. The proposed application can be used for clinical evaluation of the left ventricle mechanical function. Likewise, the results can be taken as the first step of processing for optic flow estimation algorithms.

## 1. INTRODUCTION

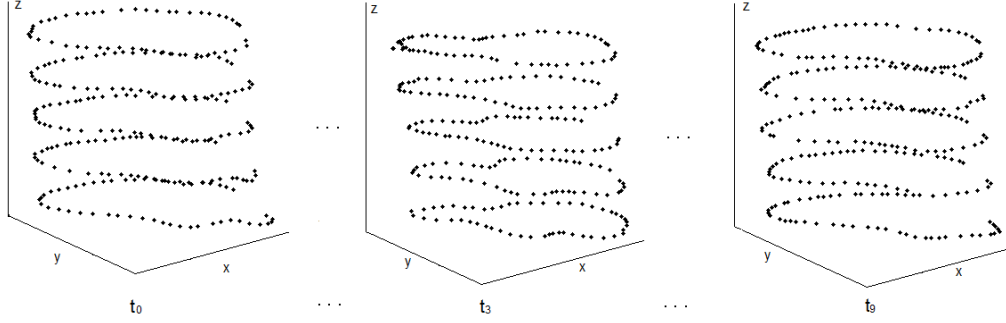
Cardiac computed tomography is one of the main types of radiological images for heart analysis and detection of abnormalities. It provides image slices or tomograms of the heart that form a tridimensional object. Since the heart is an organ with a periodic movement, analysis with cardiac CT can be made in 4D as well, which consists of several 3D images taken to reveal the complete cardiac cycle of the heart. Specialists use these studies to evaluate the mechanical function of the heart. Because the evaluation of the heart structures using cardiac CT has to be made over specific areas of the images, it is necessary to carry out some segmentation task at first. Generally speaking, medical image segmentation is a prerequisite for many high-level tasks such as image analysis, computer-assisted diagnosis, geometric modeling of anatomical structures, or the construction of bio-mechanical models used for surgery simulation [1]. During decades, several algorithms for image segmentation in the field of medical application have been developed [2]. Many of them solved the problem by using statistical models [3-5]. Other set of approaches are the so called deformable models. They consist of an initial instance that can be updated according to a set of forces in the neighborhood of a point. The shape is represented by a specific quantity of points describing the object contours in the image. Cootes et al. [6] proposed a method of models that can constrain the specific range of a training set. They called them “Active Shape Models”.

Our goal is to extent 3D active shape models to represent time-series of 3D cardiac CT images. We propose an Active Shape Model-based segmentation method in which the gray level information are obtained from the training set in order to optimize the image search.

## 2. PROPOSED ASM-BASED ALGORITHM FOR 4D OBJECTS (3D + TIME)

In this section, we outline the proposed solution to address the segmentation problem of time-varying three-dimensional structures. The most common cases of this problem are the 4D cardiac CT images which are the objective of this work. It is known that three-dimensional images in

medical applications are formed by a specific number of slices or 2D images. We assume that there is a set of time series of 3D objects previously segmented. They are represented by a set of points over each slice and describe the contour of the structure to be trained. In our application, the data (the time series of cardiac CT) are composed by a total of ten volumes (see figure 1) and the shape corresponds to the contour of the left ventricle of the heart. The ten volumes describe the complete cardiac cycle of the heart from systole to diastole.



**Figure 1.** Landmarks for the time-series of 3D objects

We start our method by accommodating the points of the time sequence as a vector. Because the sequence of volumes is our “temporal shape”, this vector must include all the landmarks for each volume. The concatenation begins with the first point of the time volume  $t_0$  and ends with the last point of the time volume  $t_9$ . The mathematical representation of each temporal shape is as follow:

$$S_i = (x_{0t_0}, y_{0t_0}, z_{0t_0}, x_{1t_0}, y_{1t_0}, z_{1t_0}, \dots, x_{(n-1)t_0}, y_{(n-1)t_0}, z_{(n-1)t_0}, \dots, x_{0t_9}, y_{0t_9}, z_{0t_9}, x_{1t_9}, y_{1t_9}, z_{1t_9}, \dots, x_{(n-1)t_9}, y_{(n-1)t_9}, z_{(n-1)t_9})^T \quad (1)$$

where  $(x_{nt_k}, y_{nt_k}, z_{nt_k})$  is the coordinate of the point  $n$  in the time  $t_k$ . As it can be seen, the resulting vector that represents the time-series is of 30th dimension. The following steps for the training process are described in [6]. Having organized the training vectors, we choose one of them as the initial mean temporal shape; the rest are aligned by using the Procrustes method [7]. Continuing with the training, covariance matrix and PCA of the aligned vectors are computed to finally build the Point Distribution Model. This model is not able to capture the complete variability of the cardiac CT structures if we do not have enough training samples.

## 2.1 Computing the gray level statistics

For the active search in the segmentation process, we need a gray level model for every landmark’s profile. Assume that  $P_{k,t_n}$  is the  $k$ -th landmark for the  $n$ -th volume of the time-series. A profile normal to the surface in this point can be defined as:

$$g_{k,t_n} = \{(P-l)_{k,t_n}, (P-l+1)_{k,t_n}, \dots, P_{k,t_n}, \dots, (P+l-1)_{k,t_n}, (P+l)_{k,t_n}\} \quad (2)$$

where  $l$  defines the extremes of the profile to each side of the principal point and follows a normal direction to the landmark. The size of the profile must be chosen as well. Most of the

time, applications have to deal with the contrast problems in the images and poor definition of edges, we choose to work with the normalized derivative  $dg_{k,t_n}$  of the profile. The mean profile and its mean normalized derivative for the  $k$ -th landmark are calculated from the samples of the training set as:

$$\bar{g}_{k,t_n} = \frac{1}{N} \sum_{i=1}^N g_{ik,t_n}, \quad , \quad \bar{dg}_{k,t_n} = \frac{1}{N} \sum_{i=1}^N dg_{ik,t_n} \quad (3)$$

Finally, the gray model is completed with the covariance matrix of the profile for each landmark of the time-sequence vector, including the profile and its normalized derivative:

$$Y_{k,t_n} = \frac{1}{N-1} \sum_{i=1}^N (g_{ik,t_n} - \bar{g}_{k,t_n})(g_{ik,t_n} - \bar{g}_{k,t_n})^T, \quad dY_{k,t_n} = \frac{1}{N-1} \sum_{i=1}^N (dg_{ik,t_n} - \bar{dg}_{k,t_n})(dg_{ik,t_n} - \bar{dg}_{k,t_n})^T \quad (4)$$

where  $T$  represents the transpose of the vector and  $N$  the number of training samples.

## 2.2 Objective function in the active search

In the active search used for image segmentation, it is necessary to define an objective function that determines the best positions where the landmarks of the initial shape have to be moved in order to better fit the data. When working with medical images, it is very common to find problems related to the contrast and noise what make difficult to carry out some tasks such as segmentation. ASM algorithms start the process of segmentation by putting, manually or in automatic way, an initial instance as closed as possible to the structure to be segmented. Each landmark is moved to a better position in the normal direction by minimizing the objective function. Giving the differences of contrast, the noise and the temporal behavior of 4D cardiac CT images, we proposed a weighted sum of Mahalanobis distances of the gray profile and its normalized derivative as objective functions for each point:

$$f_{P_{ki}} = w_1(g_{P_{ki}} - \bar{g}_k)Y_{P_k}^{-1}(g_{P_{ki}} - \bar{g}_k)^T + w_2(dg_{P_{ki}} - \bar{dg}_k)dY_{P_k}^{-1}(dg_{P_{ki}} - \bar{dg}_k)^T \quad (5)$$

where  $w_m$  ( $m = 1, 2$ ) is the assigned weight for each part of the objective function,  $P_k$  ( $k = 1, 2, \dots, n$ ) indicates the respective landmark and  $i$  represents a specific position of the landmark  $P_k$  along its normal profile. Hence, the new positions of the points are finally chosen according to the minimal value obtained for the function  $f_{P_k}$  evaluated in the normal direction of  $P_k$ . When new positions are determined, the process continues with the alignment of the initial shape and the one defined for the new landmarks. Here, angle of rotation, translation vector and a scaling factor are computed. These variables correspond to pose parameters of the data. New modifications are still necessary to adjust the data in order to reach the found solution; shape parameters are subsequently obtained in terms of the transformation matrix (rotation, translation and scaling) and eigenvectors calculated in the training stage. The final shape is calculated from the initial one by using the pose and shape parameters. Since it is an iterative process, the final result is the initial shape the next iteration.

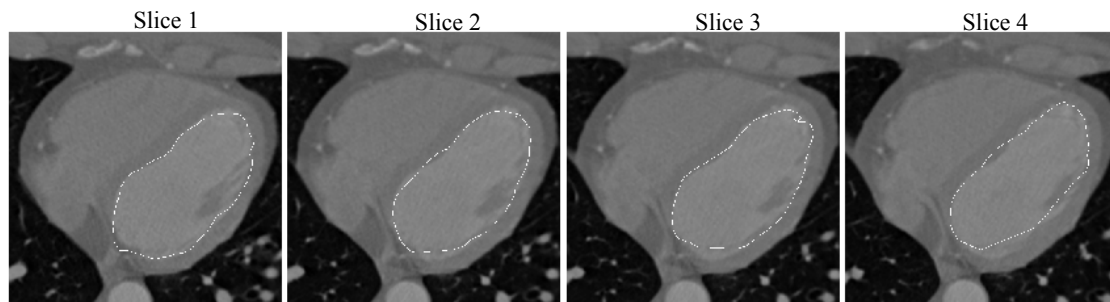
## 3. EXPERIMENTS AND RESULTS

We evaluated our method for several time-series of cardiac CT images. The structure used for the segmentation was the left ventricle of the heart from an axial view. The initial instance for each test corresponds to the mean shape of the training and it is put manually onto the time-

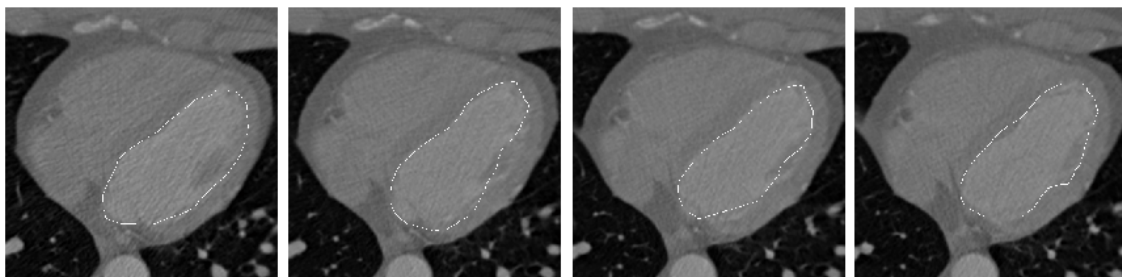
sequence. The segmentation algorithm is computed for images that were not used in the training process. We carried out visual and quantitative performance evaluations of the automatic segmentation for each sample. For the quantitative assessment, we used a metric given by the mean Euclidian distance per point which is an easy but effective method that can measure the mean separation of each point of the shapes. In our evaluation, we then calculate the distance between the automatic (for the first and final iterations) and manual segmentations of the temporal shapes. In this project, results are given for eight 4D cardiac CT images. In table 1, the obtained performance for all the samples is summarized.

**Table 1.** Characteristics of the samples and Euclidean distance between the automatic and manual segmentations.

Sample	Volumes of the Time-Series	Slices Segmented	Mean Euclidean Distance/point of the Initial Instance	Mean Euclidean Distance/point of the Final Result
Time-Series 1	10	5	5.45735	5.19752
Time-Series 2	10	5	4.47716	4.08912
Time-Series 3	10	5	3.95231	3.58310
Time-Series 4	10	5	4.12130	3.74103
Time-Series 5	10	5	2.95268	2.71527
Time-Series 6	10	5	3.60540	3.11042
Time-Series 7	10	5	3.59310	3.44656
Time-Series 8	10	5	4.93335	4.25979



a)



b)

**Figure 2.** Final segmentation of the time-series shown in figure 3, a) Volume 1; b) Volume 2

As reflected in table 1, the ASM proposed model presents good results for segmentation of cardiac CT time-series images. The obtained performance is improved when the quantity of training samples is increased. For this project we used 70 times series of cardiac CT for the PDM construction. This results in 43 eigenvectors that encode the complete variability of the left ventricle of the heart. Figure 2 illustrate the final segmentation for a 4D cardiac CT image used in which is shown the first two of the ten volumes of the time-serie. The initialization is made manually by putting the mean temporal shape resulting from the training near the object. For each slice we used 50 points around the contour of the left ventricle in an axial view. Since the objective of the proposed approach is to adapt it to optic flow estimation algorithms for mechanical evaluation of the heart, we only selected 5 slices per volume. This means that the time-series is represented by 2500 points.

#### 4. CONCLUSIONS

We have built an ASM-based method for segmentation of 4D cardiac computed tomography images. The goal of the project is to address automatic segmentations of the left ventricle and the structures around it, which is helpful to evaluate the heart mechanical functions. The proposed approach presents good results when enough training samples are used. This is a disadvantage of ASM models due to the fact that the quantity of eigenvectors defines how many deformations the shape in the active search can suffer. On the other hand, the initialization must be good enough to reach the final solution. We opted for manual initialization although automatic methods can be used as well. The method was validated with eight time-series of cardiac CT images. The algorithm was compared with manual segmentations by calculating the mean Euclidean distance of each point. From the experimental findings, we realized that using a combination of the gray profile statistics and their derivative function improves significantly the performance of the segmentation.

#### ACKNOWLEDGMENTS

This work has been sponsored by the following UNAM grant: PAPIIT IN113611 and CONACYT México. Barba-J thanks COLCIENCIAS Colombia for financial support in the project.

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