

# The Study of Applicability of the Decision Tree Method for Contouring of the Left Ventricle Area in Echographic Video Data

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**Abstract.** Echocardiography is a widespread method for analysing of the heart muscle, in which a consistent set of frames with instant images of the heart are received. Cardiologists build a contour, which bound an area of the left ventricle for each frame, because its state gives the information to diagnose diseases of the heart muscle. Doctors have an idea about the regular contour shape. They sometimes ignore some contrasting tissue on the picture and they construct parts of the contour on not contrasting areas of the image. Thus, the analysis results are dependent on the experience of the particular doctor, and therefore, to some extent, are subjective. In this context, the task of automating contouring of the left ventricle on an ultrasound image is relevant. The article discusses the experience of using machine learning method (decision trees) for the automatic identification of the left ventricle region on ultrasound images of the apical four-chamber-projection of the human heart. The list of pixels attributes used in machine learning are submitted. The results of the application of decision trees, as well as quantitative assessments of the quality of delineation of the left ventricle, are shown.

**Keywords:** contouring, left ventricle, echocardiographic images, image processing, machine learning, decision trees.

## 1 Introduction

Echocardiography is one of the cheapest non-invasive methods of diagnosing heart disease using ultrasound (US) images. The left ventricle (LV) of the heart represents a particular interest to cardiologists, since most of various pathologies and heart diseases change, primarily, its state.

For assessment the state of LV, cardiologist builds the contour, bounding region of LV, for each frame of the ultrasound images sequence, usually in manual mode.

There are many different ultrasound scanners, each of which is equipped with toolkit for the LV contouring (Philips, Aloka Hitachi, Toshiba, Siemens, General Electric, and others.). However, as the analysis of commercial offers the above-mentioned companies, there is no devices for echocardiography with built-in programs, which would allow to carry out delineation of LV in fully automatic mode.

Also, numerous studies have been conducted and various contouring algorithms have been developed. However, these articles [17, 7, 3, 6, 8] describe a problem to delineate MRI image data only. This task is more simple, because the MRI image is clear, the amount of noise is minimized. Also in [9] showed an algorithm to highlight the contour on the 3D ultrasound image. These algorithms can not be used to solve our problem. Studies have been conducted on the automation of the process of left ventricle delineation using tracking algorithms [4, 10, 13]. However it was managed to develop only a semi-automatic algorithm, which requires the participation of an expert. Thus, today the task of fully automatic LV contouring algorithm for the 2-D ultrasound images is relevant.

The purpose of this paper is to analyze the applicability of the decision tree method to automate the process of the delineation of the left ventricle on the video sequence.

## 2 Classification of Data

### 2.1 Statement of the Problem

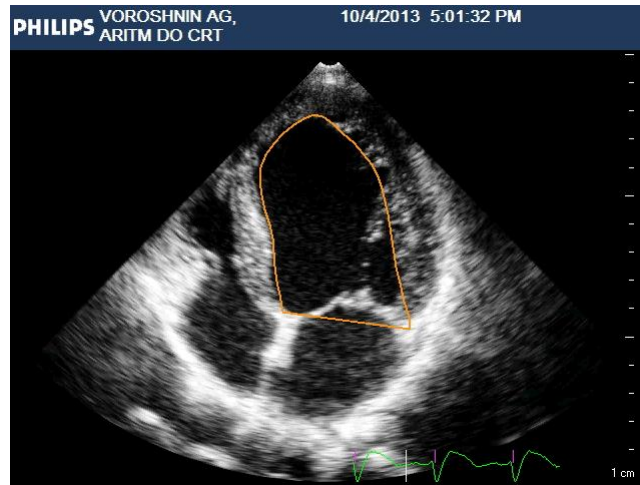
There is a set of ultrasound images in RGB space (hereinafter referred to as frames) 640 480 pixels of apical four-chamber heart projection. For each frame there is a corresponding binary frame with expert area of LV. The example of frame with LV boundaries, designated by expert, is shown in figure 1.

Each frame is a set of pixels with known coordinates  $(x, y)$  and the halftone intensities  $I \in [0, 255]$  :

$$I = 0,2989 \cdot R + 0,5870 \cdot G + 0,1140 \cdot B, \quad (1)$$

where R, G, B - are the brightness components of a pixel in RGB-space.

The analysis of expert experiment of LV area contouring showed, that the doctor builds a border, relying on their own understanding of the correct shape of the contour, ignoring some of the contrasting fabric of images and constructing additions to the border areas of the frame with a low signal to noise ratio. However, algorithmization action of expert in the construction of some of the boundaries of the LV circuit fails. For the automation of procedures of the LV contouring, it requires an additional frames analysis algorithms, such as machine learning, which can be used in this task in accordance with the following algorithm:



**Fig. 1.** The example of ultrasound image of the heart with the expert contour of LV

1. Training of the classifier:

- Formation of the initial set of pixels  $X = x_1, \dots, x_L$  (training sample), belonging to the corresponding frames in which experts noted the LV border.
- Selecting the features that characterize the pixel:  $\bar{f} = (f_1, f_2, \dots, f_J)$ , including signs of belonging of pixel to LV area ( $f_i$ )
- Marking pixels as belonging to LV area ( $f_i = 1$ , if the pixel belongs to the field of LV and  $f_i = 0$  in the opposite case).
- Forming a set of features  $F = \{\bar{f}_1, \dots, \bar{f}_L\}$ , where  $f_i$  - is the vector containing characteristic values of i-th pixel.
- Construction of the classifier in the form of a decision tree [2, 14, 16] using the set of features F pixels training sample.

2. Classification of frame pixels:

- Calculation of the features values, characterizing pixel, for each classified pixel of a frame:  $\bar{f} = (f_1, f_2, \dots, f_{L-1})$ .
- The calculation of the features values of belonging to the LV area  $f_L$  for each pixel of the frame based on a decision tree.
- Isolation of the left ventricle contour on the frame as the boundaries of classified area.

Of the above algorithm it can be seen that one of the most important stages is the stage of the classifier training. Methods of the classifier training based on decision tree, that takes into account the features of analyzed images, considered in the next section.

### 3 Methods of Learning

As the vector coordinates of the pixel features were selected Cartesian coordinates of the pixel  $x, y$  ( $f_1 = x, f_2 = y$ ), and the values of the intensity of the pixel in the frame, treated with one of following image processing methods [11, 12]:

1. Histogram equalization of the image pixels intensity;
2. Adaptive transformation of local contrasts;
3. Local range of image(rangefilt);
4. Local standard deviation of image;
5. The boundaries detection using the Sobel operator;
6. The boundaries detection using the Prewitt operator;
7. The boundaries detection using the Roberts operator;
8. The boundaries detection by looking for zero-crossings after filtering the original image with a Laplacian of Gaussian filter;
9. The boundaries detection by looking for zero-crossings after filtering the original image with a Canny operator;
10. The boundaries detection using the Canny operator.

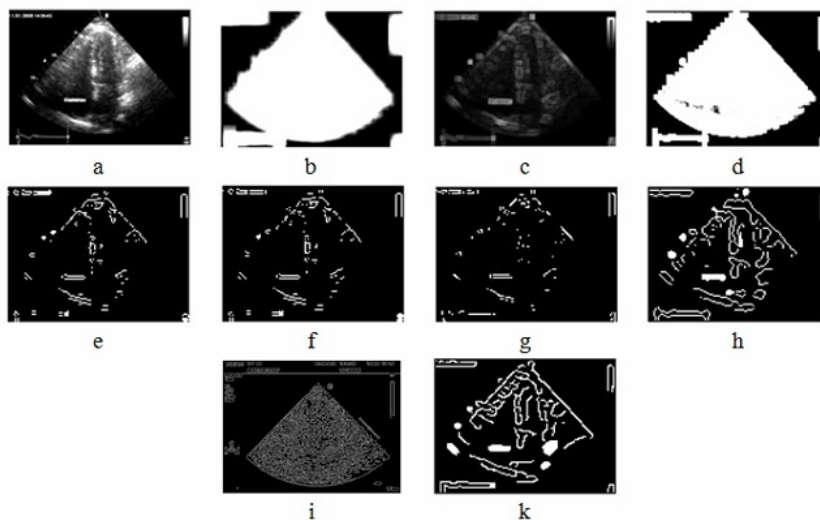
Thus, the selected vector of features  $F$  belongs to a 13-D space ( $J = 13$ ):

$$F = (x, y, I_k, f_{13}); k = \overline{1, 10}$$

The results of applying these methods to the image in Figure 1, shown in Figure 2. To train the classifier a data set was used consisting of 662 frames with a resolution of  $640 \times 480$ , since the dimension of the feature space is very large, the density of each of frame was reduced by 100 times ( $64 \times 48$ ) while maintaining the geometric dimensions of the frame. As a result, the cardinality of set of frames is equal to 26437632. Typical features pixels values of classified images are presented in table 1.

**Table 1.** Example of a table with features

| Pixel  | Feature |    |    |      |    |      |   |   |   |    |    |    |    |
|--------|---------|----|----|------|----|------|---|---|---|----|----|----|----|
|        | 1       | 2  | 3  | 4    | 5  | 6    | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 628401 | 27      | 49 | 42 | 5.68 | 30 | 11.8 | 0 | 0 | 0 | 0  | 0  | 0  | 1  |
| 628402 | 27      | 50 | 34 | 5.60 | 22 | 7.3  | 0 | 0 | 0 | 0  | 0  | 1  | 1  |
| 628403 | 27      | 51 | 38 | 5.29 | 48 | 12.7 | 0 | 0 | 0 | 0  | 0  | 1  | 0  |
| 628404 | 27      | 52 | 30 | 4.90 | 35 | 14.4 | 0 | 0 | 1 | 1  | 1  | 1  | 0  |



**Fig. 2.** Image processing results, a) histogram equalization of the image pixels intensity, b) The entropy of the image, c) Local range of image, d) Local standard deviation of image, e) Sobel operator, f) Prewitt operator, g) Roberts operator, h) - The boundaries detection by looking for zero-crossings after filtering the original image with a Laplacian of Gaussian filter, i) - The boundaries detection by looking for zero-crossings after filtering the original image with a Canny operator, k)- Canny operator

Evaluation of training using the decision tree method was done using the cross-validation procedure:

1. The resulting table of features was divided into 10 equal-sized blocks  $\{B_i\}$ ,  $i = \overline{1, 10}$ .
2. Test block  $B_k$ ,  $k = \overline{1, 10}$  has consistently selected from  $\{B_i\}$ , and a plurality of blocks  $\{B_i\} \setminus B_k$  used as a training sample.
3. The estimate of the average values of the error (the share of misclassified pixels) of all tested samples was calculated using cross-validation.

When classifying pixels resulting errors can be divided into two groups:

- error of the first kind - a pixel belonging to the area of the left ventricle, is classified as not belonging to it;
- error of the second kind - the pixel does not belonging to the area of the left ventricle, is classified as belonging to her.

A numerical estimate of error includes errors both the first and the second kinds.

Average classification accuracy of pixels by 10 blocks was 0.9866, respectively, the average error of classification was - 0.0134.

There is the ROC-curve, constructed for this classifier, shown in Figure 3. The index of AUC was 0.9715.

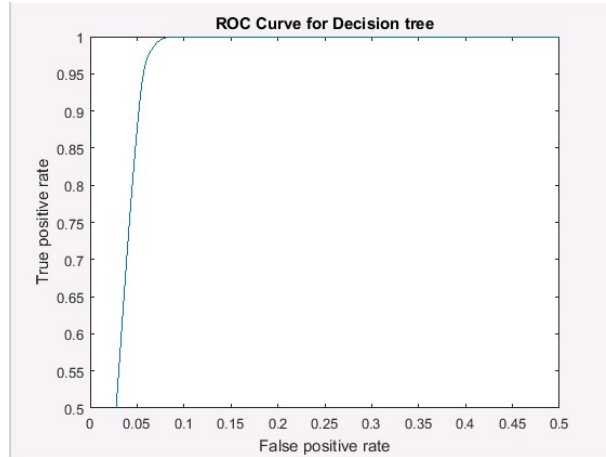


Fig. 3. ROC-curve for a decision tree classifier

#### 4 Assessment of the Quality of Construction LV Area

Assessment of the quality of construction of the LV area was done based on the same sample of 662 frames (17 patients). To train the classifier 620 frames were used of 16 patients (94%). Testing was conducted on the remaining 42 frames of the last (17) patient (6%).

Example of the LV region, formed by qualified pixels using a decision tree, is shown in Figure 4.

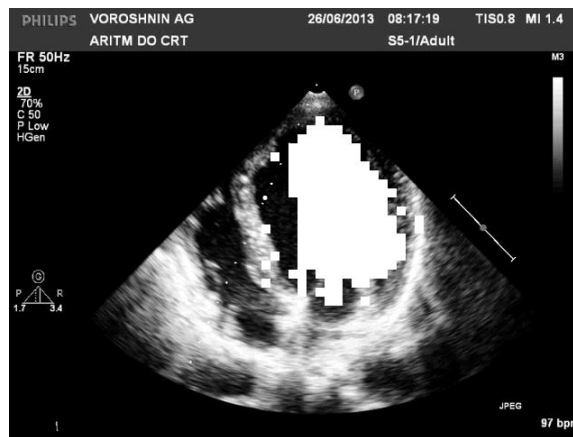
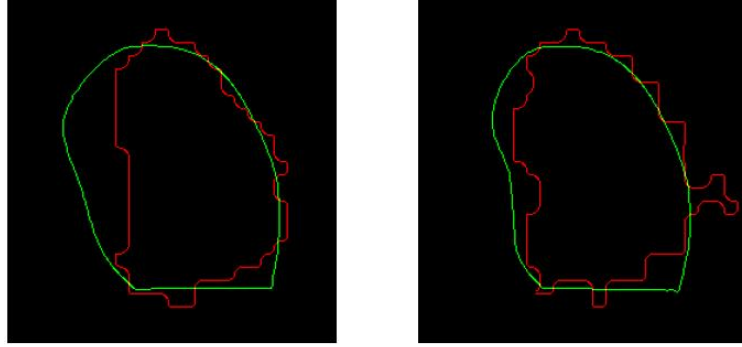


Fig. 4. Example of LV area, built with the help of the decision tree

Classified area was transformed into LV contour for further evaluation as follows:

1. The removal of pixels distant from the main area;
2. Morphological processing by operation "closure" with the structuring element "disk" a radius of 3 for smoothing the area;
3. Detecting the contour from the resulting area.

Examples of the contour and the corresponding expert contour presented in Figure 5.



**Fig. 5.** Image of the expert contour (green) and the contour constructed according to the algorithm (red).

Figure 5 shows that the contours are significantly different. In this context, the quantitative assessment of the quality of the left ventricle contouring was held. For this purpose the following criteria were used:

- cross validation [1, 5]
- area under the curve
- precision

$$K = \frac{S_{\cap}}{S_{cont}},$$

where  $S_{\cap}$  - is the intersection of square of area, limited by expert contour, and area, formed from classified pixels,  $S_{cont}$  - square of the area, formed from the classified pixels.

- recall

$$Recall = \frac{S_{\cap}}{S_{exp}}$$

where  $S_{exp}$  - is the area of the region bounded by the expert contour.

- F-measure

$$F = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

- is the coefficient of the kinematic center of mass (CM) of the left ventricle area in the video sequence of frames with flexing of the heart muscle of patient

$$K = \frac{S_{ellipse}}{S_{diast\_cont}}$$

were  $S_{ellipse}$  - is the area of the ellipse, bounding CM LV,  $S_{diast\_cont}$  - is the area of the region contour in diastole.

Estimates for the coefficient of CM motion in patients with pathologies and without pathologies are given [15].

The results of these criteria are presented in table 2.

**Table 2.** Quantitative assessment of the quality of contouring.

| Criteria   | Assessment |
|------------|------------|
| Recall     | 0.77±0.01  |
| Precision  | 0.92±0.02  |
| F          | 0.84       |
| K          | 0.001      |
| Validation | 0.9865     |
| AUC        | 0.9715     |

## 5 Conclusions

In the studies examined the use of one of the machine learning methods (decision tree) in the problem of the development of the automatic delineation algorithm of the heart left ventricle to the echographic video sequences.

Quantitative assessment of the quality of learning were made. The following values of criteria were received: Precision - 0.92, Recall - 0.77, F-measure - 0.84 coefficient of kinematics CM - 0.001.

According to the results it can be concluded that the contour, derived from the classified LV region, is unsatisfactory due to the fact that it significantly differs from the expert contour. (Values of precision, recall and F-measure for satisfactory contour close to 1.) In this regard, the algorithm requires further research, the purpose of which:



- determine the usefulness of each feature in the training set and reduce the dimension of feature space using only the most informative features;
- explore the use of other well-known machine learning algorithms within the task.

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