Segmentation of the Left Ventricle in Cardiac MRI Using an ELM Model

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Abstract In this paper, an automatic left ventricle (LV) segmentation method based on an Extreme Learning Machine (ELM) is presented. Firstly, according to background and foreground, all sample pixels of Magnetic Resonance Imaging (MRI) images are divided into two types, and then 23-dimensional features of each pixel are extracted to generate a feature matrix. Secondly, the feature matrix is input into the ELM to train the ELM. Finally, the LV is segmented by the trained ELM. Experimental results show that the mean speed of LV segmentation based on the ELM is about 25 times faster than that of the level set, about 7 times faster than that of the SVM. The mean values of *mad* and *maxd* of image segmentation based on the ELM is about 80 and 83.1 % of that of the level set and the SVM, respectively. The mean value of *dice* of image segmentation based on the ELM is about 8 and 2 % higher than that of the level set and the SVM, respectively. The standard deviation of the proposed method is the lowest among all three methods. The results prove that the proposed method is efficient and satisfactory for the LV segmentation.

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1 Introduction

Cardiovascular disease is one of the main reasons of death over the past decades in
the world. Cardiac magnetic resonance imaging (MRI) has proven to be a versatile
and noninvasive imaging modality. Some techniques are used for the diagnoses of
heart diseases. The MRI of the left ventricle (LV) is very important for the
assessment of stroke volume, ejection fraction, and myocardial mass, as well as
regional function parameters such as wall motion and wall thickening [1]. To
perform a quantitative analysis of a LV, doctors need an accurate segmentation of
the LV which can provide the anatomical and functional information of a heart, so it
can be widely applied in clinical diagnoses [2, 3]. The segmentation of cardiac MRI
images is one of the most critical prerequisites for quantitative study of the LV.

So far, in clinical practice, the segmentation of the LV is almost completed
manually. This workload, however, is too heavy and time-consuming, subjective
and irreproducible. Therefore, it is attractive to develop accurate and automatic
segmentation algorithms for clinical applications.

This paper is organized as follows. Section 2 briefly reviews the related works on
the segmentation of LV. In Sect. 3, this paper introduces the basic theory of ELM.
In Sect. 4, the image segmentation methods are introduced in detail. The experi-
mental results of the segmentation of LV based on the ELM are presented in
Sect. 5. In Sect. 6, the conclusions are offered.

2 Related Works

In recent years, many methods have been proposed for LV segmentation. They can
be classified into two types: deformable models and image-based methods.
A complete review of recent literature is given in [3].

Deformable models include snakes [4–6], level set [7, 8], and their variants
[9–11]. Deforming curves are derived iteratively in accordance with the mini-
mization of an energy function which is composed of a data-driven term. A random
active contour scheme for automatic image segmentation was proposed in [12].

Image-based approaches include thresholding [13], pixel-based classification
[14–16], region-based and edge-based approaches. Otsu approaches [17] were
employed by Lu [18] and Huang [19] in LV segmentation of cardiac MRI. How-
ever, the Otsu approach, which is based on the histogram of objects in the image,
could be biased from the optimal threshold [20]. Dynamic programming

(DP) approach is used to find boundaries of the LV in MRI images [21, 22]. However, due to the complex boundaries of the myocardium [23], the performance of the DP approach sometimes is poor in boundary extraction.

3   A Brief Introduction to the Extreme Learning Machine

The extreme learning machine (ELM) is a learning algorithm, whose speed can be thousands of times faster than traditional feedforward network learning algorithms, and which has better generalization performance [24].

Given N arbitrary different samples (X_i, t_i), where $X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$, and $t_i = [t_{i1}, t_{i2}, \ldots, t_{im}]^T \in R^m$, standard SLFNs with M hidden nodes and activation function $g(x)$ are modeled as

$$\sum_{i=1}^{M} \beta_i g_i(x_j) = \sum_{i=1}^{M} \beta_i g(w_i \cdot x_j + b_i) = o_j \quad (j = 1, \ldots, N) \tag{1}$$

where M is the number of the hidden layer nodes, $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ is the input weight vector, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ is the output weight vector, and b_i is the threshold of the ith hidden node. $w_i \cdot x_j$ is the inner product of w_i and x_j [24].

If only the activation function is infinitely differentiable, the input weights and hidden layer biases can be randomly generated [24]. All the parameters of SLFNs need to be adjusted; training an SLFN is simply equivalent to finding a least squares solution $\widehat{\beta}$ of the linear system $H\beta = T$:

$$\left\| H(w_1, \ldots, w_M, b_1, \ldots, b_M)\widehat{\beta} - T \right\| = \min \left\| H(w_1, \ldots, w_{\tilde{N}}, b_1, \ldots, b_{\tilde{N}})\beta - T \right\|. \tag{2}$$

If the number M of the hidden nodes equals the number N of distinct training samples, matrix H is square and invertible, and SLFNs can approximate these training samples with zero error. However, in most cases the number of hidden nodes is much less than the number of distinct training samples, $M \ll N$, H is a non-square matrix and there may not exist w_i, b_i, β_i such that $H\beta = T$ where

$$H(w_1, \ldots, w_M, b_1, \ldots, b_M, x_1, \ldots, x_N) = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \cdots & g(w_M \cdot x_1 + b_M) \\ \vdots & \cdots & \vdots \\ g(w_1 \cdot x_N + b_1) & \cdots & g(w_M \cdot x_N + b_M) \end{bmatrix}_{N \times M}, \tag{3}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_M^T \end{bmatrix}_{M \times m} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N \times m} \tag{4}$$

$$\widehat{\beta} = H^{\dagger}T, \tag{5}$$

where $H^{\dagger}$ is the Moore–Penrose generalized inverse of matrix H. The ELM algorithm [24] can be described as follows [25].

Algorithm: ELM
1: for i = 1 to M do
2: randomly assign input weight w_i
3: randomly assign bias b_i
4: calculate H
5: calculate $\widehat{\beta} = H^{\dagger}T$

4   Methods

The whole algorithm of this image segmentation includes pre-processing techniques, training ELM, classification and post-processing as shown in Fig. 1.

4.1   *Pre-processing Training Data and Training ELM*

The pre-processing procedure of training data consists of the following steps:

1. Three typical images in cardiac MRI were selected as sample images.
2. All the pixels were selected from the LV of the ground truth, which were labeled as 1. The region of the LV was extended, and then all the pixels were selected from the extended region, which were labeled as 0 [26].
3. In addition to gray level value, gray mean value and gray median, representative features related to gray level co-occurrence matrix(GLCM) [27] such as energy, contrast, correlation entropy and inverse from 4 directions via a 5 × 5 window were used to represent a pixel, amounting to 23-dimentional features. Feature vectors of all pixels of an image were concentrated to generate a feature matrix.
4. Pre-processing procedure of each image includes steps 2–4, three feature matrices were merged into a feature matrix at last, whose values are normalized to [0, 1].

The training ELM is to find optimal parameters. The ELM kernel used in the pro-posed algorithm is Sigmoid function and the number of hidden nodes is 100, which are selected through multiple trials and means the optimal performance. Owing to the randomness of the input weights and hidden layer biases, in order to find the optimal input weights and hidden layer biases to gain optimal segmentation performance, therefore, the segmentations of images were performed over and over.
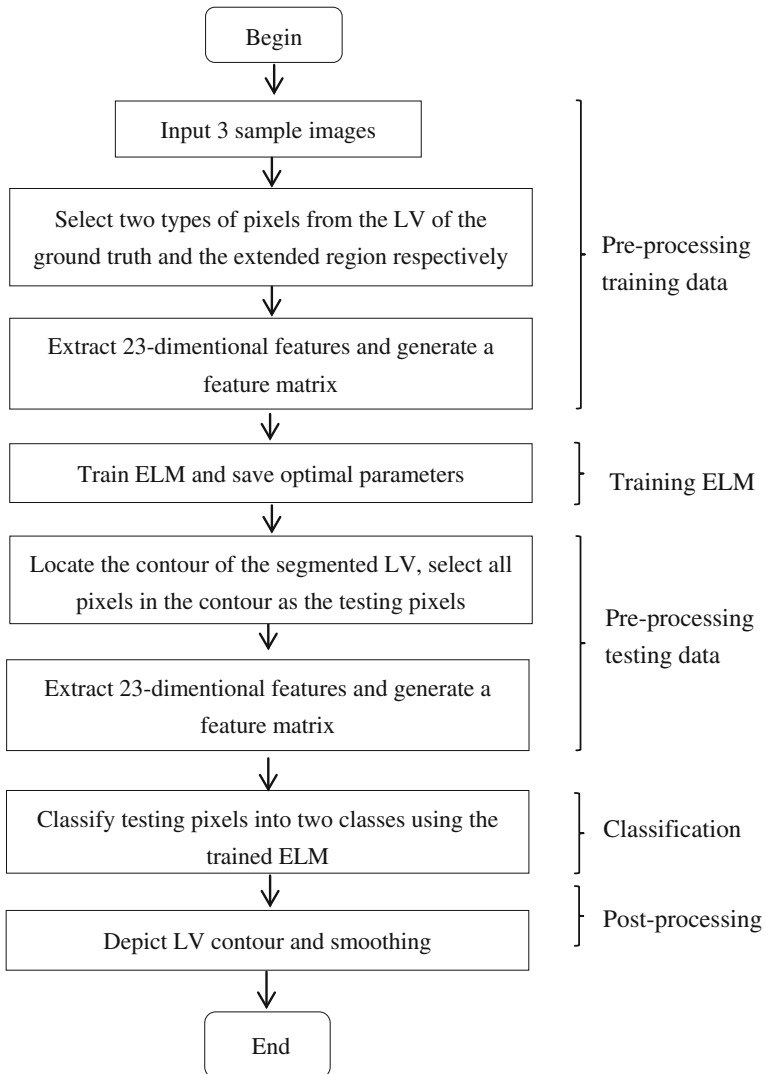
Fig. 1 Workflow of the proposed segmentation algorithm

4.2 Pre-processing Testing Data

The pre-processing procedure of testing data consists of the following steps:

1. A fitting threshold of the image was found using the Otsu method, and then the original image was converted into a binary image.
2. Little objects in the binary image were removed, whose areas are less than 300 pixels. The contours of the remaining objects were depicted.
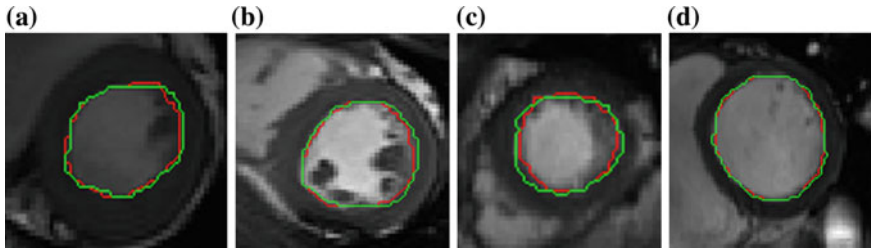
Fig. 2 ELM segmentation results of images (**a–d**). *Green* and *red* contours are obtained with manual and automatic segmentation, respectively

3. Due to the shape of LV approximating a circle, the roundness of each remaining object was calculated, and then the object which owned the biggest roundness is the LV, the LV was located approximately.
4. Usually, the errors of the contour of the LV aren't satisfactory, therefore, the morphological methods were used to process the contour, and as a result, the processed LV con tour included almost all the pixels of the LV regarded as the testing pixels set.
5. By the same methods (introduced in Sect. 4.1) 23-dimentional features of each pixel of the testing pixels set were extracted to generate a feature matrix.

4.3 Classification and Post-processing

All pixels were classified into two classes by using the trained ELM, namely one class belongs to the LV and the other one belongs to the non-LV. The LV contour was depicted and smoothed using the open-close operation in mathematical morphology, the segmentation results are shown in Fig. 2.

5 Results

5.1 Evaluation Measures

In this paper, a convenient tool for researchers is adopted to test and compare the segmentation results of the proposed method; the level set method and the SVM method easily and objectively. From the point of view of accuracy, several measures are used in our experiments, including mean absolute deviation (MAD), maximum absolute deviation (MAXD) and Dice Similarity Coefficient (DSC).

5.2 Performance

In this section, the performance of LV segmentation based on an ELM is studied through evaluating its efficiency and effectiveness. The algorithms are coded in MATLAB. All experiments are conducted on a 3.2-GHz PC with 4G memory running window 7. Real datasets are used in the experiments. The dataset includes a total of 1000 images whose sizes are 216×256 or 256×216.

Figures 2, 3 and 4 illustrate the segmentation results of the proposed method, the level set method and the SVM method of images (a), (b), (c), (d), respectively. The segmented LVs are delineated by red pixels. Green contours are obtained by manual segmentation. Many experiments were conducted on image segmentation based on the ELM. Among these experiments, the optimal performance is obtained, when the number of hidden layer nodes equals 100, and activate function is Sigmoid function.

Table 1 lists *mad*, *maxd*, *dice*, and time of our proposed method, the level set method and the SVM method about 24 images, respectively. From Table 1, it can be seen that the mean *mad* of proposed method is about 0.64 pixels, its standard deviation is about 0.18 pixels, the mean *maxd* of the proposed method is about 2.25 pixels, its standard deviation is about 0.71 pixels and the mean *dice* of the proposed
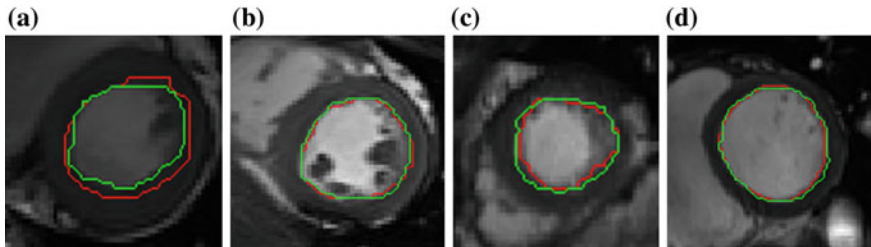

Fig. 3 Level set segmentation results of images (**a–d**). *Green* and *red* contours are obtained with manual and automatic segmentation, respectively
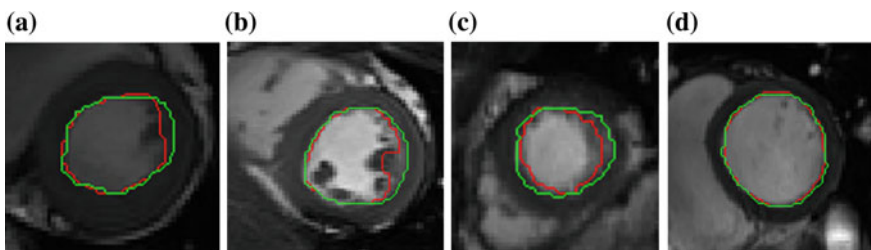

Fig. 4 SVM segmentation results of images (**a–d**). *Green* and *red* contours are obtained with manual and automatic segmentation, respectively

Table 1 Segmentation accuracy and speed on the ELM, the level set, the SVM

Id	Mad			Maxd			Dice (%)			Time		
	#1	#2	#3	#1	#2	#3	#1	#2	#3	#1	#2	#3
1	0.50	0.66	0.80	1.41	2.00	2.24	95	88	91	0.73	9.30	3.67
2	0.50	0.51	0.70	1.41	2.00	2.00	95	89	91	0.73	8.41	2.42
3	0.99	0.57	0.60	3.16	2.24	2.24	87	88	92	0.19	7.94	2.11
4	0.63	0.98	0.77	2.00	2.83	3.00	91	83	89	0.16	8.72	1.64
5	0.65	0.97	0.65	2.24	2.83	2.00	92	82	92	0.27	7.89	2.17
6	0.62	0.85	0.64	2.00	2.24	1.41	92	84	92	0.25	8.14	2.14
7	0.35	0.65	0.53	1.41	2.00	1.41	96	91	95	0.28	8.53	3.23
8	0.24	0.67	0.77	1.41	2.24	2.00	96	85	88	0.31	8.56	1.76
9	0.54	1.41	0.77	2.00	3.00	3.00	92	81	88	0.25	9.30	1.70
10	0.47	0.49	0.32	2.83	1.41	1.00	95	90	97	0.33	9.11	3.01
11	0.53	0.62	0.44	1.41	2.00	1.41	92	85	93	0.31	9.33	1.78
12	0.67	0.63	0.75	3.61	3.61	4.00	90	84	89	0.31	8.85	1.86
13	0.70	1.12	0.96	2.00	8.54	4.12	93	84	90	0.41	8.88	3.15
14	0.58	0.48	1.14	2.00	1.41	7.00	93	89	85	0.34	9.63	2.36
15	0.74	0.77	0.83	2.24	2.24	2.00	92	87	91	0.39	8.75	3.17
16	0.52	0.77	0.53	2.00	2.24	2.00	95	87	94	0.44	8.33	3.24
17	0.89	0.63	0.74	3.00	2.00	2.24	90	89	91	0.42	9.41	2.81
18	0.95	0.49	0.54	3.00	1.41	3.00	88	89	93	0.44	8.81	2.61
19	0.80	1.30	1.08	2.83	4.00	3.16	91	79	87	0.45	9.22	2.59
20	0.66	0.79	0.89	2.24	2.24	2.83	93	86	90	0.48	8.63	2.93
21	0.71	0.91	0.75	2.24	2.24	2.24	92	84	91	0.56	8.89	2.90
22	0.50	0.61	0.49	1.41	1.00	1.41	94	88	94	0.58	8.97	2.67
23	0.80	0.78	1.34	2.24	2.24	3.00	86	79	77	0.56	9.11	1.73
24	0.81	1.41	1.35	4.00	5.39	5.39	89	74	82	0.53	9.42	2.45
Mean	0.64	0.80	0.77	2.25	2.64	2.67	92	85	90	0.36	8.84	2.50
Std	0.18	0.27	0.26	0.71	1.53	1.34	2.67	4.05	4			

#1 denotes the ELM method, *#2* denotes the level set method, *#3* denotes the SVM method

method can reach up to 92 %, its standard deviation is about 2.67 %. The mean computation time of the proposed method is 0.36 s.The proposed method runs about 25 times faster than the level set method, about 7 times faster than the SVM method. The *dice* of image segmentation based on the ELM is about 8 and 2 % higher than that of the image segmentation based on the level set and the SVM, respectively. The standard deviation of our proposed method is the lowest in all three methods.

In order to further evaluate the performance of the proposed method, the local distributions of segmentation errors and the similarity between the segmentation and the ground truth have been illustrated in Fig. 5, respectively. The boxplots indicate the median, lower and upper quartiles of *mad*, *maxd*, *dice* of the above
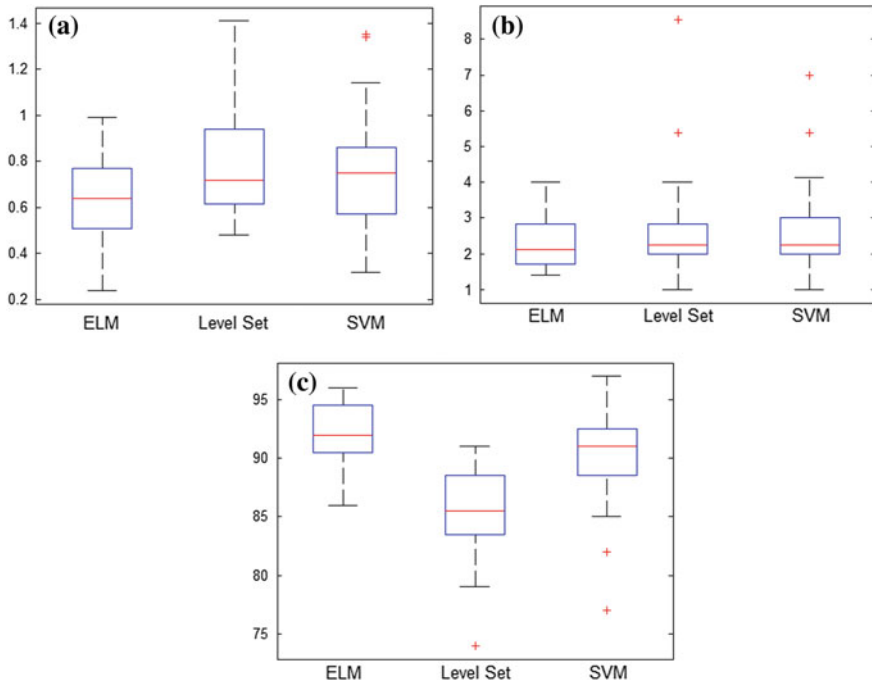
Fig. 5 Box plots of *mad* (**a**), *maxd* (**b**), and *dice* (**c**) between the ELM method, the level set method and the SVM method

three methods directly. It can be seen from Fig. 5 that the proposed method outperforms the other two methods since it obtains the higher *dice* and the lower *mad* and *maxd* than the other two methods.

6   Conclusions

This paper describes a new automatic LV segmentation method based on an ELM in cardiac MRI images in short-axis MRI view. This method takes into account the intensity inhomogeneity which often occurs in the left ventricular cavity and may cause many difficulties in image segmentation. Some images processing methods such as the morphological dilatation and the open-close operation in mathematical morphology have been used in the procedures of segmenting MRI images. Firstly, in accordance with background and foreground all the sample pixels were divided into two classes and then 23-dimensional features of each pixel were extracted to generate a feature matrix. Secondly, an ELM was trained using the feature matrix. Finally, the LV image was segmented using the trained ELM. Experimental results show that the mean speed of LV segmentation based on the ELM is about 25 times

faster than that of the level set method, about 7 times faster than that of the SVM method, and in terms of the *mad* metric, *maxd* metric and *dice* metric, the image segmentation based on the proposed method is slightly better than those of the level set method and the SVM method. The results of this study prove that the proposed method is efficient and satisfactory for segmentation of LV.

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