

Evolving Fuzzy Image Segmentation

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Abstract—Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label are connected and meaningful, and share certain visual characteristics. Pixels in a region are similar with respect to some features or property, such as color, intensity, or texture. Adjacent regions may be significantly different with respect to the same characteristics. Therefore, it is difficult for a static (non-learning) segmentation technique to accurately segment different images with different characteristics. In this paper, an evolving fuzzy system is used to segment medical images. The system uses some training images to build an initial fuzzy system which then evolves online as new images are encountered. Each new image is segmented using the evolved fuzzy system and may contribute to updating the system. This process provides better segmentation results for new images compared to static paradigms. The average of segmentation accuracy for test images is calculated by comparing every segmented image with its gold standard image prepared manually by an expert.

Keywords— *Image segmentation, Evolving fuzzy systems, SIFT.*

I. INTRODUCTION

Evolving fuzzy systems are a recent approach used in many applications to solve diverse problems through evolution of fuzzy rules. Evolving fuzzy systems, however, have not been used for image segmentation. Their dynamic capability could improve the segmentation accuracy of different images especially for real-world applications. In this paper, we propose a method that uses evolving fuzzy systems to segment digital images. The motivation for using evolving fuzzy systems is the higher degree of adaptability to the complex and dynamic nature of the segmentation problem. The experiments are performed on breast ultrasound images.

This paper is organized as follows: In section II, SIFT will be briefly described. In section III, the literature on fuzzy image segmentation techniques is briefly reviewed. In section IV, a review of the evolving fuzzy image segmentation is provided. Section V, the proposed evolving fuzzy image segmentation is described. In section VI, the results of applying the proposed system to a set of image data is presented and analysed. Section VII summarizes the paper.

II. SCALE INVARIANT FEATURE TRANSFORM (SIFT)

SIFT is an approach developed by Lowe [1] as a method for object recognition. It depends on detecting a set of key points in an object and calculates a set of descriptors (features) for these points. These features can be used to recognize one object from among different objects. The process of detecting key points and calculating descriptors consist of four stages:

- 1) Scale-space extrema detection: it uses a difference-of-Gaussian function in different scales and locations to calculate the potential of interest points that are invariant to scale and orientation.
- 2) Key point localization: for each candidate point, a measure of their stability is performed to discard points with low contrast or poorly located along the edges.
- 3) Orientation assignment: local image gradient directions are used to assign one or more orientations to each key point location, to make sure that the candidate points are invariant to orientation.
- 4) Key point descriptor: after selecting the candidate points, the local image gradients are measured in the region around each key point.

We use SIFT method to locate the key points inside the image that seems to be the most descriptive points. The features are extracted from a rectangle around each point.

III. FUZZY IMAGE SEGMENTATION

Fuzzy approaches are relatively popular methods for image segmentation. Here we provide a brief review of fuzzy segmentation techniques that may be related to our work.

Fuzzy image segmentation has been used for processing color images. In an approach [2], the segment (separated by edges) within the image is treated as a fuzzy set and can grow using fuzzy criteria. Moreover, the edge detection and region growing algorithms are combined to find larger segments. In a different approach [3], fuzzy c-mean (FCM) and principle component analysis are combined to segment color images using eigen-based membership fuzzy function.

Karmakar et al. [4] propose a generic fuzzy rule-based segmentation technique that tries to solve the problem of manual selection of the parameters of the fuzzy membership in previous fuzzy segmentation techniques. This proposed technique is unlike the previous fuzzy segmentation as it is application-independent and incorporates spatial relationships between pixels.

Tao et al. [5] present a new algorithm for image segmentation by a three-level thresholding technique based on maximum fuzzy entropy and genetic algorithms. They divide the image into three parts and determine the width and attribute of the fuzzy region by maximizing fuzzy entropy. They use a genetic algorithm to find the optimal combination of all parameters.

Cinque et al. [6] suggest a modification to the existing fuzzy approach for image segmentation adaptive reasoning theory (ART) model. They state that their proposed approach solves the problems of the existing ART model such as overfitting, complexity and inability to measure the extent of match between any two patterns.

Zhang et al. [7] suggest a new algorithm that uses a kernel-induced distance metric instead of the original Euclidean distance in the FCM and adding a spatial penalty on the membership functions to modify the objective function in the fuzzy C-means (FCM). They use their approach for segmentation of magnetic resonance imaging (MRI) data.

Cai et al. [8] propose a new fuzzy c-means clustering algorithm that combines spatial and gray-level information of the image for image segmentation. They called their algorithm fast generalized fuzzy c-means (FGFCM).

Fuzzy clustering is used for segmenting noisy images. That could be done by combining the spatial information which is the summation of the membership functions in the neighbourhood of each pixel under consideration of the image into the membership function for clustering [9]. In a different method, Fuzzy Tree Algorithm is used to represent the data (spatial) and the path compression which helps in reducing the CPU time [10]. In another approach, a modification of the existing fuzzy c-means is used to segment noisy images [11].

Zhuge et al. [12] present a fuzzy connected-based image segmentation to segment vectorial images. Their technique extends the previous work on scalar images to vectorial images. They apply their method on arbitrary dimensional vectorial medical MR images.

Dou et al. [13] propose a fuzzy fusion technique to segment brain tumours in MR images automatically. They suggest to build a separate fuzzy model for each type of MRI image that they may have some prior information about. The different fuzzy models are then fused into one model.

Ma et al. [14] present a modification to the fuzzy C-means image segmentation algorithm to be used with uneven illumination patterns. They insert biased illumination field estimation to the existing recursive FCM algorithm. Moreover, they used the intensity and average intensity of a pixel neighbourhood to define new clustering centre and fuzzy clustering functions and to dilate the initial segment to improve the segmentation process.

Han et al. [15] propose an improvement of the Ant Colony Algorithm (ACA) previously used in image segmentation but with high complexity. They suggest to improve the algorithm to reduce the computation time in image segmentation with a modified fuzzy clustering method.

Hata et al. [16] propose a fuzzy technique for the segmentation of the endorhachis in magnetic resonance images. This algorithm checks the possibility of the endorhachis regions in the image and gives the higher possibility a high fuzzy degree. Moreover, they describe a fuzzy maximum intensity projection (FMIP) technique that maps the higher fuzzy membership degrees to brighter values in the data set.

Fan et al. [17] propose a new remote sensing image seg-

mentation approach that solves the problems of the clustering quality caused by the position of the initialization of the cluster centroids in the existing fuzzy C-means algorithm. They suggest to use a single point iterative procedure in the fuzzy C-means clustering to segment remote sensing images.

Foo et al. [18] propose a fuzzy rule-based image segmentation method to mark tumours in a three-dimensional CT data using initial selection of a region of interest (ROI) by the user.

Di Martino et al. [19] use fuzzy transform technique to compress images and then use the Fast Generalized Fuzzy C-Means clustering algorithm to segment the compressed images.

All previous fuzzy segmentation techniques used fuzzy rules and fuzzy clusters, or combined fuzzy rules with other techniques such as principle component analysis approach (PCA) to segment images. There is still need for a fuzzy method that can update the fuzzy rules during the segmentation process. Such dynamic approaches may help in improving the segmentation accuracy and reduce the time required for updating the rules manually.

IV. EVOLVING FUZZY SYSTEMS

Evolving fuzzy systems are a rather recent development used for many applications. Fuzzy rules could evolve using different methods either by combining with neural networks or genetic algorithms or other techniques that update the fuzzy rules online. Evolving fuzzy rules have not been used for medical image segmentation. We provide here a review of evolving fuzzy systems and their applications.

Kasabov [20] proposed evolving fuzzy neural networks that can learn and perform reasoning, rule extraction and aggregation online. This network is applied to a bench-mark problem. The evolving fuzzy neural network system uses locally tuned elements to perform the process of incremental online learning. When there are more data, the network should be updated by pruning of the nodes, or aggregation of nodes. The network consists of five layers with nodes that are created and connected when data becomes available. The authors compare their algorithm with the fuzzy neural networks and the knowledge-based neural networks.

Futschik et al. [21] use evolving fuzzy neural networks to overcome the problem of transparency in the classification process of the existing statistical and machine learning methods. They used the evolving fuzzy neural networks to classify cancer tissue. They extract fuzzy rules associated with genes that are evidence of specific types of cancer.

Rivas et al. [22] propose a method to design fuzzy membership functions and fuzzy rules using evolutionary computation. They state that their design is simultaneous and its elements are mutually dependent. They also develop an algorithm that is applied directly to the data structure of the fuzzy logic system instead of a binary representation.

Angelov [23] proposed a fuzzy controller of Takagi-Sugeno type with evolving structure. He proposed a new technique for online identification of Takagi-Sugeno systems. He uses the data collected during the process of control to build up the Fuzzy rules of the structure of the controller. The fuzzy

controller is trained using the data collected during the process of control in a non-iterative, recursive way. He provides an example from air-conditioning systems to explain his method.

Chang et al. [24] propose a new hybrid model to forecast the future sales of a printed circuit board factory. They use Self Organization Maps (SOM) along with a Genetic Algorithm (GA) and Fuzzy Rule-Based system to build their hybrid model. They reduced the interaction between fuzzy rules by clustering the fuzzy rules into different clusters. They optimize the number of fuzzy terms of the input and output which turns the fuzzy rules into evolving fuzzy rules. Chang et al. [25] propose an approach that uses a weighted evolving fuzzy neural network system to forecast the future sales of printed circuit board.

Rong et al. [26] use the functional equivalence between a radial basis function network and a fuzzy inference system to develop a sequential adaptive fuzzy inference system. The proposed algorithm is an adaptive technique that depends on the input data to decide whether to add or remove a fuzzy rule from/to the fuzzy rule base.

Xydeas et al. [27] propose two new models to solve the problem of the classification of the brain signals (electroencephalogram (EEG)). They use dependant hidden Markov models to represent the inputs in their first method. In the second method, they use a recursive, online, and evolvable fuzzy rule base to classify the EEG signals.

Lin et al. [28] propose a self-adaptive neural fuzzy network with group-based symbiotic evolution to be used in prediction applications. Their approach contains a self-clustering algorithm (SCA) that addresses the internal structure in which the number of clusters (fuzzy rules) is equal to the true number of clusters in a given training data set. They use a group-based symbiotic evolution learning method that is used to get the desired output by adjusting the parameters.

Barros et al. [29] propose a model that makes an online identification of computationally undemanding evolving fuzzy models. They propose an approach that models non-linear dynamic systems using an online evolving fuzzy model. The rule base is built via incremental learning when accepting new input by adding new rule or deleting, updating existing rule base.

Linden et al. [30] use evolving fuzzy rules and genetic algorithm (in which the rules are represented as an expression in reverse Polish notation) to extract rules from micro array data. They apply their algorithm to problems arising in the construction of gene regulatory networks.

Angelov et al. [31] proposed an evolving fuzzy classifier using different model architectures. They suggest two different approaches for online evolving fuzzy classifiers that could work with different model architectures. Moreover, their first approach can have a multi-input-multi-output architecture. They apply their approach on handwriting recognition and, real-life problem of image classification.

Phan et al. [32] propose a direct self-structuring adaptive fuzzy control approach for affine nonlinear single-input-single output systems. This approach is a self-structuring approach

that adds new membership functions and rules to adjust the system and reduce the number of rules by replacing the old membership functions by new ones.

Du et al. [33] study the application of evolving Takagi-Sugeno fuzzy model to non-linear system identification. The authors use genetic algorithm to propose a new encoding approach for learning the Takagi-Sugeno model. They suggest to represent the rules and the inputs and membership functions of the fuzzy system in one chromosome to be evolved.

Lai et al. [34] propose an evolving fuzzy decision tree for financial time series data forecasting for stocks in Taiwan Stock Exchange Corporation. They build a decision-making system by combining a clustering technique, a fuzzy decision tree, and genetic algorithms.

Lughofer [35] study the application on surface inspection using two different on-line evolving image classifiers. The first one is a supervised classification approach that uses conventional vector quantization and forming an incremental evolving variant around it.

Juang et al. [36] provide a dynamic system processing using recurrent self-evolving fuzzy neural network with local feedbacks. Their approach is an online approach that uses a learning process of the structures (generating the fuzzy rules online) and the parameters. A Kalman filter is used to learn the consequent parameters. As well, a gradient descent algorithm is used to learn the antecedent parameters.

V. EVOLVING FUZZY IMAGE SEGMENTATION

The idea of evolving fuzzy image segmentation is straightforward: generate a rule-base for segmentation and then let the rules evolve to reach or maintain a high accuracy level.

We start with a set of training images randomly selected from the available set of test images along with their gold standard image. The algorithm should start with **extracting features**. For this purpose we use a set of points detected by the SIFT within a rectangle around the region of interest in these training images. We focus on the simplest form of segmentation, namely thresholding. A set of initial fuzzy rules can be built using the features of the training images as antecedent and their optimal threshold values as consequent. The remaining images in our test set are segmented using the initial fuzzy rules. Based on the quality of the result for any new image, the initial fuzzy rules are evolved. This process is repeated multiple times as long as new images coming, rules are updated. This should increase the segmentation accuracy of the coming new images. The results of segmentation of new images are recorded by calculating the average accuracies by comparing it with its gold standard image prepared manually by an expert.

A. Detection Algorithm

Since features would make more sense if they are calculated for the “region of interest”, all images are first processed by a detection algorithm which finds the position of the first seed point inside the region of interest and create a rectangle R around this point. The algorithm performed as follow:

- The seed point P is calculated by tracing a 10×10 mask over the image I and calculating the sum and the standard deviation of every mask and the correlation between the mask and its neighbour. Based on empirical knowledge about our test images, the region of interest has low gray-level intensities and generally a low standard deviation. The mask that has minimum sum and minimum standard deviation is considered the mask contains the seed point. The correlation coefficients between the mask and its preceding mask are used to select the mask containing the seed point if the minimum sum and minimum standard deviation are in two different masks. Hence, for every 10×10 part of the image the minimum sum, standard deviation and correlation are considered to mark the position of a seed point inside the region of interest.
- The algorithm proceeds by constructing a rectangle around the region of interest using the point P as the center of the rectangle. Based on the empirical knowledge, the algorithm starts by finding a region around P as a $n \times n$ window (e.g. 100×100) and incrementally enlarges the window (e.g. with 10×10). This process stops when the standard deviation of one window becomes greater than or less than the standard deviation of the previous region by a certain limit ϵ (e.g. 3%); the last window is considered the region of interest R . These images are stored to be used for extracting feature in the training and testing phases. In most images, the detection algorithm detects a correct point inside the region of interest. For other images, it failed to detect a correct point but we proceed with the rectangle generated by the algorithm.

B. Training Phase

In this phase, we start with the process of feature extraction then the initial fuzzy system will be built (Fig. 1).

1) *Feature Extraction*: The proposed technique starts with extracting a set of features from training images and uses these features to assign best thresholds to different images using a fuzzy system consisting of fuzzy rules. The process of extracting features is performed as follow:

- The algorithm randomly selects 5 of 20 medical images (breast ultrasound scans) as a training set and the remaining 15 images are used for testing.
- For each training image, the rectangle R around the region of interest created by the detection algorithm is used.
- The rectangle around the region of interest R is provided to the SIFT algorithm which then returns a set of key points $p_1, p_2, \dots, p_n$ within the rectangle R .
- For each key point assigned by SIFT a 40×40 rectangle is constructed around the point and a set of features are extracted.
- For each image, the optimal threshold is calculated in order to be used for rule generation.

We use simple features that can be calculated fast:

- The mean gray-level μ_S for each 40×40 rectangle S around each key point generated by SIFT: The average

gray-level of a sub-image is an indication of its darkness/brightness.

- The standard deviation σ_S for each 40×40 rectangle S around each key point generated by SIFT: The intensity variation captured by the standard deviation quantifies our confidence in darkness/brightness of the sub-image.
- The distance $d_S = \max S - \min S$ between the maximum and the minimum of each 40×40 rectangle S around each key point generated by SIFT: This distance provides additional information to distinguish between different variation levels captured by standard deviation.

Using the SIFT guarantees that the features are extracted in regions with invariant significant characteristics.

2) *Building the Initial Fuzzy System*: The initial fuzzy system is built from a set of images randomly selected from the set of available images. The input to the fuzzy system consists of the three features calculated around each key point generated by SIFT:

- The mean gray-level μ_S
- The standard deviation σ_S
- The distance $d_S = \max S - \min S$ between the maximum and the minimum of each 40×40 rectangle S .

For each training image, SIFT assign n points inside the region of interest. The features are extracted and calculated from every training image from the rectangles around the n points assigned by SIFT. All features are recorded in a matrix called *Input* matrix. The Input matrix consists of three columns describing the three features and number of rows is equal the number of SIFT points in each image multiplied by the number of training images. In our case, we use five images for training, and the SIFT technique detects ten key points in every image. So the Input matrix has $5 \times 10 = 50$ rows.

The Output (optimal threshold) is a matrix consisting of the optimal thresholds for every training image.

We used the Matlab function “genfis” to generate the rules from the data. The *genfis* function takes two parameters, namely the Input and the Output matrix. A general example for the rules generated is as follows:

IF (μ IS μ_1) AND (σ IS σ_1) AND (d IS d_1)
THEN (Threshold IS $th1$)

C. Testing phase

After building the initial fuzzy system using randomly selected images, the remaining set of test images can be segmented using the evolving fuzzy system (Fig. 1) which can be described as follows:

- 1) For each image, the rectangle R around the region of interest created by the detection algorithm is used.
- 2) The rectangle R is fed into SIFT which returns a set N of key points inside R .
- 3) The set of features are now calculated from a 40×40 rectangle around each point in N .
- 4) For every coming new image,
 - The extracted features from every point are used to run the initial fuzzy system which assigns the image a threshold for each point in N .

- The extracted features are stored to be added to the Input matrix later.
 - The threshold T^* for segmenting the image is calculated by taking the average of all thresholds for each point $n_i \in N_1$: $T^* = \frac{1}{|N_1|} \sum_{i=1}^{|N_1|} T_i$
 - For each Image, the assigned threshold is used to segment the image I .
 - The thresholded image is presented to an expert to judge its quality. The expert's evaluation may be:
 - a) The threshold is too high (threshold adjustment set to $\Delta = -25$), OR
 - b) The threshold is high (threshold adjustment set to $\Delta = -15$), OR
 - c) The threshold is low (threshold adjustment set to $\Delta = +15$), OR
 - d) The threshold is too low (threshold adjustment set to $\Delta = +25$).
 - The adjusted thresholds along the newly extracted features are inserted to the Output and Input matrices, respectively.
 - The new Input and Output matrices are used in the Matlab function "genfis" to evolve the initial fuzzy rules.
 - The next new image is segmented using the newly generated rules and the process repeated.
- 5) After finishing all test images, the average of segmentation accuracy and other statistics are now calculated.

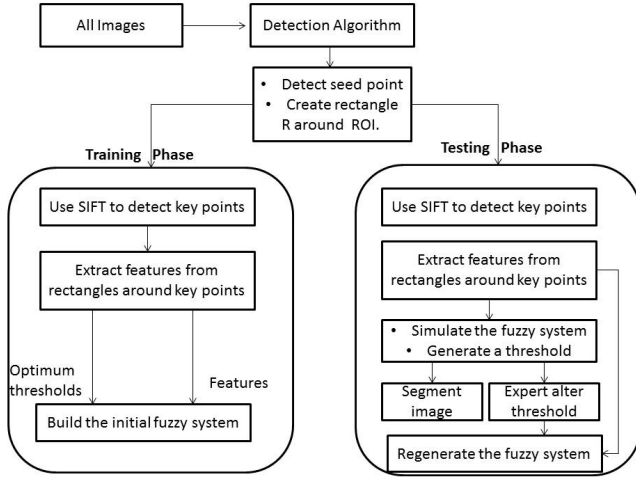


Fig. 1. The evolving fuzzy segmentation

VI. EXPERIMENT AND RESULTS

The proposed approach randomly selects 5 of 20 medical images as a training set and the remaining 15 images are used for testing. All results of 10 different training sets are calculated and recorded in the Table I.

The following metrics have been employed to verify the performance of the proposed approach (A and B are two segments, one of them being the gold standard):

- 1) The Dice coefficient D of segmentation accuracy,

$$D(A, B) = \frac{2 * |A \cap B|}{|A| + |B|} \quad (1)$$

- 2) The standard deviation σ_D of the Dice coefficient.
- 3) The average of segmentation accuracy J is calculated using the area overlap (also called Jaccard Index)

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (2)$$

- 4) The standard deviation σ_J of the Jaccard index.
- 5) The confidence interval (CI) of Jaccard index CI_J .
- 6) The null hypothesis (T-test) between the fuzzy results and the evolving fuzzy results helps to ensure that they are really different.

Sample results of the proposed algorithm are shown in Figure 2. In all images, there is a high improvement in the segmentation accuracy when applying the evolving fuzzy proposed algorithm compared with the ordinary fuzzy rule-based segmentation.

Generally, it is obvious from the Table I that the proposed algorithm performs segmentation more accurately than the conventional fuzzy algorithm. The proposed algorithm has the highest segmentation accuracy and the lowest standard deviation in all training sets. For example, in the fourth training set, the segmentation accuracy increases from 64% in the fuzzy segmentation to 74% in the proposed evolving fuzzy segmentation, and the standard deviation decreased from 25% to 18%. On the other hand, the dice value increased from 75% to 84% and its standard deviation decreased from 22% to 14%. Moreover, the 95% confidence interval of the Jaccard index increased from 50%-78% to 64% - 84%. As well, the 95% confidence interval of the dice value increased from 63%-88% to 76% - 92% which means that the proposed system is more consistent. The validation of the null hypothesis indicates that in the half of the training sets the segmentation accuracy improved.

VII. CONCLUSIONS

An evolving fuzzy system was used to segment images by updating the fuzzy rules. Initial fuzzy rules were generated and then updated online. Initial fuzzy rules were created from a number of images randomly selected from the available image set of medical images. The remaining set of images was segmented using the initial fuzzy rules. New images were segmented using the evolving fuzzy rule base. Based on expert's evaluation, the new rules were calculated for every new image and used to evolve the existing fuzzy rules to segment the following images more accurately. Results show clear improvements in segmentation accuracy.

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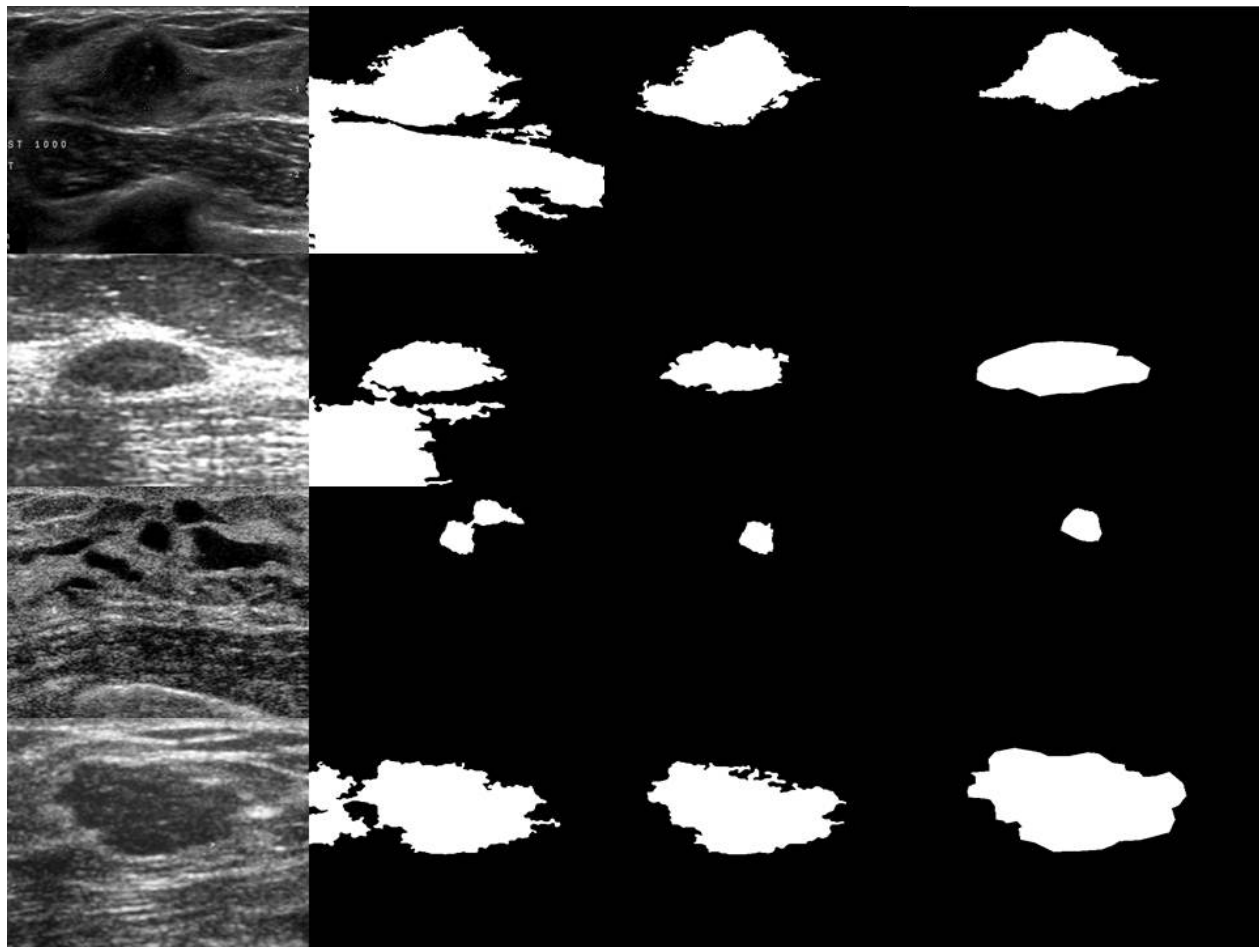


Fig. 2. Sample results (from left to right): original image, fuzzy results, evolving fuzzy results, and corresponding gold standard images.

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TABLE I

SUMMARY OF THE RESULTS FUZZY SEGMENTATION (FS) AND EVOLVING FUZZY SEGMENTATION (EFS): JACCARD INDEX J (ACCURACY), ITS STANDARD DEVIATION σ_J AND 95%-CONFIDENCE INTERVAL CI_J , THE DICE COEFFICIENT D (ACCURACY), ITS STANDARD DEVIATION σ_D AND 95%-CONFIDENCE INTERVAL CI_D .

Training Set	Method	J	σ_J	CI_J	D	σ_D	CI_D	$NullHypo.$
First Training set	FS	70%	24%	57%-84%	80%	20%	69%-92%	0
	EFS	70%	24%	57%-84%	80%	20%	69%-92%	
Second Training set	FS	58%	27%	43%-74%	70%	25%	56%-84%	1
	EFS	73%	19%	62%-84%	83%	16%	73%-92%	
Third Training set	FS	61%	24%	48%-75%	73%	21%	61%-85%	0
	EFS	67%	25%	53%-81%	77%	22%	65%-90%	
Fourth Training set	FS	64%	25%	50%-78%	75%	22%	63%-88%	1
	EFS	74%	18%	64%-84%	84%	14%	76%-92%	
Fifth Training set	FS	61%	24%	47%-74%	72%	21%	60%-84%	1
	EFS	71%	23%	58%-84%	81%	20%	69%-92%	
Sixth Training set	FS	73%	20%	62%-85%	83%	18%	73%-93%	0
	EFS	77%	18%	67%-87%	86%	16%	77%-95%	
Seventh Training set	FS	72%	23%	59%-85%	81%	20%	70%-93%	0
	EFS	73%	23%	60%-85%	82%	20%	70%-93%	
Eighth Training set	FS	55%	29%	39%-71%	66%	26%	52%-81%	1
	EFS	71%	23%	58%-84%	81%	20%	69%-92%	
Nineth Training set	FS	51%	28%	36%-67%	63%	26%	49%-78%	1
	EFS	64%	23%	51%-77%	75%	20%	64%-87%	
Tenth Training set	FS	63%	27%	48%-79%	74%	25%	60%-88%	0
	EFS	72%	24%	59%-86%	81%	20%	70%-93%	

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