Self-Configuring and Evolving Fuzzy Image Thresholding

A. Othman¹, H.R. Tizhoosh², F. Khalvati³

¹ Dept. of Information Systems, Computers & Informatics, Suez Canal University, Egypt, a.othman@ci.suez.edu.eg

² KIMIA Lab, University of Waterloo, Canada, tizhoosh@uwaterloo.ca

³ Dept. of Medical Imaging, Sunnybrook Research Institute, University of Toronto, Canada, farzad.khalvati@sri.utoronto.ca

Abstract—Every segmentation algorithm has parameters that need to be adjusted in order to achieve good results. Evolving fuzzy systems for adjustment of segmentation parameters have been proposed recently (Evolving fuzzy image segmentation – EFIS [1]). However, similar to any other algorithm, EFIS too suffers from a few limitations when used in practice. As a major drawback, EFIS depends on detection of the object of interest for feature calculation, a task that is highly application-dependent. In this paper, a new version of EFIS is proposed to overcome these limitations. The new EFIS, called self-configuring EFIS (SC-EFIS), uses available training data to auto-configure the parameters that are fixed in EFIS. As well, the proposed SC-EFIS relies on a feature selection process that does not require the detection of a region of interest (ROI).

I. INTRODUCTION

Evolving fuzzy image segmentation has been recently introduced to solve the parameter setting problem (e.g., fine-tuning) of different segmentation techniques. EFIS has been designed with emphasis on acquiring and integrating user feedback into the fine-tuning process. As a result, EFIS is suitable for all those applications, such as medical image analysis, in which an experienced and knowledgeable user provides evaluative feedback of some sort with respect to the quality, i.e., accuracy, of the segmentation process. Image segmentation is the grouping of pixels to form meaningful clusters of pixels that constitute objects (e.g., organs, tumours), a task with various applications in medical image analysis including measurement, detection, and diagnosis. Image segmentation can be roughly categorized into two main classes of algorithms; non-parametric (e.g., atlas-based segmentation) and parametric (e.g., region growing) algorithms. The former is based on a model which usually does not require parameters whereas the latter is based on some parameters that must be adjusted in order to obtain reasonable segmentation results. Parameterbased segmentation algorithms always face the challenge of parameter adjustment; a parameter tuned for a particular set of images may perform poorly for a different image category. On the other hand, in a clinical setting such as a hospital, the final outcome of image segmentation algorithms usually need to be modified (i.e., manually edited) and approved by a an expert (e.g., radiologist, oncologist, pathologist). The clinical ramifications of not verifying the correctness of segments include missing a target (resulting in a less effective therapy) or increased toxicity if the target is over-segmented. The frequent expert intervention to correct the results, in fact, generates valuable feedback for a learning scheme to automatically adjust the segmentation parameters. EFIS is a segmentation scheme that evolves fuzzy rules to tune the parameters of a given segmentation algorithm by incorporating the user feedback which is provided to the system as corrected or manually created segmentation results called gold standard *images*. EFIS represents a new understanding of how image segmentation should be designed in the context of observeroriented applications. Naturally, EFIS needs to be further improved and extended in order to exploit the full potential of its underlaying evolving mechanism in relation to the user feedback. The original design of EFIS as presented in [1] requires pre-configurations of a few steps which should be set for a given image set and the segmentation algorithm to which EFIS is integrated. This limits the efficiency of EFIS; either the algorithm should be pre-configured for each dataset and/or segmentation algorithm or it is possible that a fixed pre-configuration will adversely affect its performance. In this paper, we present an extended version of EFIS which we call self-configuring EFIS (short SC-EFIS) that has a higher level of automation. The new extension of EFIS proposed in this paper will enhance EFIS through removing these limitations by introducing self-configuration into different stages of EFIS.

This paper is organized as follows: In section II, a brief review of the EFIS (evolving fuzzy image segmentation) will be provided. In section III, we present the proposed selfconfiguring EFIS (SC-EFIS). In section IV, experiments are described and the results are presented and analyzed. Finally, section V concludes the paper.

II. A BRIEF REVIEW OF EFIS

The concept of Evolving Fuzzy Image Segmentation, EFIS, was proposed recently [1], [2]. The problem that EFIS attempts to address is parameter adjustment in image segmentation. The basic idea of EFIS is to adjust the parameters of segmentation to increase the accuracy by using user feedback in form of corrected segments. To do so, EFIS extracts features from a region inside the image and assigns them to the best parameters that are exhaustively detected in an offline stage or maintenance cycle. Clustering or other methods are then used to generate fuzzy rules, which are then continuously updated when new images are processed. EFIS needs to be trained for specific algorithms and image categories. In other words, in order to employ EFIS, the following components must be pre-designated:

- Parent algorithm: any segmentation algorithm with at least one parameter that affects its accuracy
- Parameter(s) to be adjusted (e.g., thresholds, scales)
- Images and corresponding gold standard images

• Procedure to find optimal parameters (e.g., brute force or trial-and-error via comparison with the gold standard images)

Once the above-mentioned components are made available, the following steps need to be specified in EFIS:

- ROI-detection algorithm: An algorithm that detects the region of interest (ROI) around the subject to be segmented by EFIS.
- Procedure for feature extraction around available seed points: Methods like SIFT are used to generate seed points. But a certain number of expressive features should be calculated in the vicinity of each seed point to be fed to fuzzy inference system.
- Rule pruning: Upon processing a new image, a new rule can be learned only if the features and corresponding output parameters had not been observed previously. In other words, by looking at the difference between an input (features plus outputs) with all rules in the database, the information of a new image is added only if not captured by existing rules.
- Label fusion: When EFIS is used with multiple algorithms at once, the segmentation results are fused using a fusion method namely STAPLE algorithm [3].

EFIS includes two main phases namely training and testing. In training phase, images with their gold standard results are fed to the algorithm where features are extracted from each image. The parent algorithm, e.g., thresholding [4], [5], [6], [7], [8], [9], [10], is applied to each image and the results are compared to the gold standard image. The algorithm's parameters are continuously changed until the best possible result is achieved. The parameter which yields the best result (i.e., the highest agreement with the gold standard image) along with the image feature extracted in the previous stage are stored. Once all training images are processed, the fuzzy rules are generated from the stored data using a clustering algorithm.

In testing phase, new images are first processed to extract features. Next, the image features are fed to the fuzzy inference system to approximate the parameters. The parent algorithm is then applied to the input image using the estimated parameter. EFIS can address both single-parametric and multi-parametric problems. EFIS was applied to three different thresholding algorithms and significant improvements in terms of segmentation accuracy were achieved [1].

III. SELF-CONFIGURING EFIS (SC-EFIS)

This section introduces a new version of EFIS, namely a self-configuring evolving fuzzy image segmentation (SC-EFIS) which represents a higher level of automation compared to the original EFIS scheme. The proposed SC-EFIS scheme consists of three phases; self-configuration phase, training phase, and online or evolving phase. In the following, each of these phases is described in detail.

A. Self-Configuring Phase

In the self-configuring phase (Algorithm 1), all available images are processed in order to determine two crucial factors:

1) the size of the feature area around each seed point, and 2) the final features to be used for the current image category.

The $Z \times Z$ rectangle around each SIFT point to be used for feature calculation is determined based on different sizes of all available images (Algorithm 1). Following this step, the set of features that should be used for the available images is selected from a large number of features which are calculated for each image from the vicinity of the SIFT points located in the entire image (since there is no longer an ROI) (Fig. 1). This process starts with the determination of the number of SIFT points N_F that should be used in the current image (algorithm 1). This step is identical to the procedure used in the EFIS training phase, as previously explained in section II, with three exceptions: the SIFT points are detected across the entire image (as opposed to selecting SIFT points inside an ROI as a subset of the image), the final number N_F of SIFT seed points is not fixed, and the points returned are separated from each other by Z in each direction. For all N_F seed points, features are extracted from a rectangle R_C around each point, based on the discrete cosine transform (D_C) of R_C , the gradient magnitude (G_M) of R_C , the approximation coefficient matrix A_C of R_C (computed using the wavelet decomposition of R_C), and the SIFT descriptors D_S . The following set of features is extracted (Algorithm 1):

- 1) The mean, median, standard deviation, co-variance, mode, range, minimum, and maximum of R_C , $D_{C_{R_C}}$, and $A_{C_{R_C}}$, and $G_{M_{R_C}}$ (32 features)
- 2) The mean, median, standard deviation, co-variance, range, minimum, maximum, and zero population of D_S (eight features) with the minimum of D_S changed to be the minimum number after zero
- The contrast, correlation, energy, and homogeneity of the gray level co-occurrence matrices (computed in four directions 0°, 45°, 90°, and 135°) of R_C, D<sub>C_{R_C}, and A<sub>C_{R_C}, and G<sub>M_{R_C} (64 features)
 </sub></sub></sub>
- 4) The contrast, correlation, energy, and homogeneity of the gray level co-occurrence matrices (computed in only one directions of 0°) of D_S (four features)
- 5) A feature matrix F_1 of size $N_F \times N_T$ generated for I (in this case $N_T = 108$)

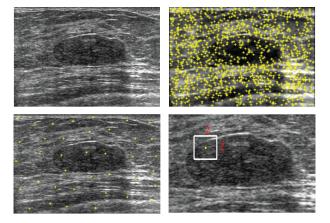


Fig. 1. Feature extraction process (from top left to bottom right): original image, seed points detected by SIFT, selected seed points via sorting the descriptor, calculating features around each selected seed point.

Algorithm 1 Self-Configuration Phase

- 1: Set the variables and initialize all matrices
- 2: Read the available images $I_1, I_2, \cdots, I_{N_I}$.
- 3: Read the size of the images, namely all rows R₁, R₂, ..., R_{NI}, and all columns C₁, C₂, ..., C_{NI}.
 4: Determine the size of the rectangle
- $Z = 0.1 \times \max(\text{median}_i(R_i), \text{median}_i(C_i)).$
- 5: Create the initial matrix F_1 and the final matrix F^* .
- 6: for each image do
- 7: Determine N_F , the number of SIFT points, that should be used for image I_i .
- 8: for each SIFT point do
- 9: Extract features f_1, f_2, \dots, f_{N_T} from the $Z \times Z$ rectangle around each SIFT point.
- 10: Append the features as a new row to the initial matrix F_1 , which becomes of size $N_F \times N_T$.
- 11: **end for**
- 12: Calculate S_T different statistics from F_1 and assigned in F_2 .
- 13: Append F_2 of the current image of size $S_T \times N_T$ to the feature matrix F_3 (the feature matrix F_3 becomes of size $L \times N_T$, $L = S_T * N_I$)
- 14: end for
- 15: Remove very similar features from F₃ (e.g., at least 99% correlated). F₄ is a reduced matrix of F₃ of size L×N_{T1}, N_{T1} ≤ N_T.
- 16: Determine the number of features by discarding similar ones from F_4 (e.g., at least 90% correlated). F_C is a feature matrix generated from F_4 of size $L \times N_{T_2}$, $N_{T_2} \leq N_{T_1}$.
- 17: Use k different unsupervised feature selection methods to generate k different feature matrices in addition to F_C : F_P , F_M , F_F , F_G , and F_L . All of these matrices are of size $L \times N_{T_2}$.
- 18: Select any features found in at least half of the matrices to form F_5 of size $L \times N_{T_3}$, $N_{T_3} \le N_{T_2}$.
- 19: Generate a final feature matrix F^{*} from F₅ by removing similar features (e.g., at least 90% correlated). F^{*} is of size L × N_L, N_L ≤ N_{T₃}.

The next step is to calculate S_T different statistical measures from F_1 (e.g., $S_T = 8$: mean, median, mode, standard deviation, co-variance, range, minimum, and maximum). The resulting matrix F_2 (size $S_T \times N_T$) is returned, in which each row represents a statistical measure (Algorithm 1, CSF). F_2 is then appended to the feature matrix F_3 (Algorithm 1). After all images are processed, the feature matrix F_3 is formed from the features of all images, with each image being represented by S_T rows. In the last step, the final set of features that should be used in the current image category are selected from F_3 . This process starts with the removal of very similar features in F_3 based on the calculation of the correlations between all features. Hence, if two features are highly correlated, e.g. with a correlation coefficient of at least 99%, then one is kept and the other is discarded. The output of this process is a matrix F_4 (Algorithm 1).

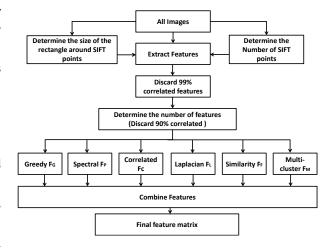


Fig. 2. The process of feature selection

Five methods, along with an additional correlation-based method, were combined to produce an ensemble of final relevant features that could be used for training (see Fig. 2): Mitra et al. [11]- F_F (feature similarity), He et al. [12]- F_L (Laplacian score), Zhao et al. [13]- F_P (spectral graph), Cai et al. [14]- F_M (multi-cluster), Farahat et al. [15]- F_G (greedy algorithm), and F_C (correlation method).

For any unsupervised feature selection technique, the number of features N_{T_2} that should be returned must be established in advance. A correlation with a threshold of 90% is used in order to determine the number of features that should be returned from F_4 (Algorithm 1). Following this process, F_C is the resulting feature matrix. In addition to F_C , five different unsupervised feature selection methods are also used for feature selection. The matrix F_4 and the variable N_{T_2} are passed to the methods, and each method returns a different matrix with its selected features. The resulting matrices are F_G [15], F_L [12], F_F [11], F_P [13], and F_M [14] (Algorithm 1). For all features in the six matrices, any feature extracted by at least three of the six methods are selected and appended to a matrix F_5 (Algorithm 1). The final matrix F^* is generated based on the discarding of features from F_5 that are at least 90% correlated (Algorithm 1).

B. Offline Phase

In the offline phase, the best parameters for segmenting each image are calculated through an exhaustive search and then stored in matrix T (Algorithm 2). The process is performed as explained in [1].

C. Training Phase

In this phase, the features selected for the training images are used for the training of the fuzzy system. A set of images are randomly selected for training (Algorithm 2). A matrix M is created and filled with the rows from F^* that belong to the training images (Algorithm 2). A matrix O is created and filled with the rows from T that belong to the training images (Algorithm 2). A pruning step is performed starting from the second training image in order to ensure that Mand O do not contain similar rows (Algorithm 2). The pruned

Algorithm 2 Offline and Training Phases

- 1: ——— Offline phase ———
- 2: Determine the parent algorithm(s) and their parameters p_1, p_2, \cdots, p_k .
- 3: Read the gold standard images G_1, G_2, \dots, G_n .
- 4: Via exhaustive search or trial-and-error comparisons with gold standard images, determine the best segments S_1, S_2, \dots, S_n and the best parameters $p_1^*, p_2^*, \dots, p_k^*$ that generate the best segments and store them in matrix T.
- 5: Training phase
- 6: Determine the available training images $I_1, I_2, \cdots, I_{N_R}$.
- 7: Create two empty matrices M for input and O for output.
- 8: for all N_R images do
- 9: Fill matrix F_T with rows from matrix F^* that belong to the training image I_i $(F_T = F^*(I_i))$.
- 10: Fill matrix T_R with rows from matrix T that belong to the training image I_i
- $(T_R = T(I_i)).$
- 11: **if** i=1 **then**
- 12: Append F_R to M, and T_R to O.
- 13: **else**
- 14: Pruning step: Discard rows from F_R and T_R that are similar to rows in M and O, respectively.
- 15: Append the updated matrices F_R and T_R to M and O respectively.
- 16: end if
- 17: **end for**
- 18: Generate fuzzy rules R_{F_1}, R_{F_2}, \cdots from the input matrix M and the output matrix O (e.g., using clustering).

matrices M and O are used for the generation of the initial fuzzy rules (Algorithm 2). The initial fuzzy system is built through the creation of a set of rules using the Takagi-Sugeno approach to describe the in- and output matrices. Based on N_L different features from the input and one optimal parameter as the output, a set of rules is generated whereby the features are in the antecedent part and the optimal parameters are in the consequent part of the rules.

D. Online and Evolving Phase

The evolving process is performed in order to increase the capabilities of the proposed system. For each test image, a matrix F_S is filled with the rows from F^* that belong to the test image (Algorithm 3). Fuzzy inference using F_S is applied, and a parameter vector T_O is returned (size 1×8) and the final output parameter T^* is calculated (Algorithm 3). The resulting parameter is used for the segmentation of the image (Algorithm 3), and the resulting segment is stored and then displayed to the user for review and eventual correction (Algorithm 3). The best parameter for the current image is then calculated based on the user-corrected segment and is stored in T_B (Algorithm 3). A pruning procedure is performed on F_S and T_B as described in [1], with the exception that the Euclidean distance thresholds are, in contrast to EFIS, different for different techniques. After pruning, revised versions of F_S and T_B are appended to M and O (Algorithm 3). In the final

Algorithm 3 Online/Evolving Phase

- 1: Load the fuzzy rules R_{F_i} and the matrices M, O, and F^* .
- 2: Load the test images $I_1, I_2, \cdots, I_{N_E}$.
- 3: for all N_E images do
- 4: Fill matrix F_S with the rows from matrix F^* that belong to the test image I_i ($F_S = F^*(I_i)$).
- 5: Perform fuzzy inference to generate output: $T_O = \text{FUZZY-INFERENCE}(R_{F_1}, R_{F_2}, \cdots).$
- 6: Generate a single output T^* from T_O using the mean of T_O (μ_{T_O}), the median of T_O (M_{T_O}), the fuzzy membership (m_{T_O}) of the standard deviation of T_O (σ_{T_O}) using a Z-shaped function (zmf) $m_{T_O} = zmf(\sigma_{T_O}, [(\mu_{T_O} * 0.10) \ (\mu_{T_O} * 0.20)])$, and $T^* = m_{T_O} * \mu_{T_O} + (1 - m_{T_O}) * M_{T_O}$.
- 7: Apply the parameters to segment I_i .
- 8: Display segment S and wait for user feedback (user generates a gold standard image G by editing S)
- 9: —— *Rule Evolution Invisible to User* —
- 10: Determine the best output vector $p_1^*, p_2^*, \dots, p_k^*$ (via comparison of S with G) and store it in T_B .
- 11: Pruning Discard rows from F_S and T_B that are similar to rows in M and O, respectively.
- 12: Append the matrices F_S and T_B to M and O, respectively.
- 13: Generate fuzzy rules R_{F_i} from the updated matrices M and O (e.g., using clustering).

14: **end for**

step, the current fuzzy inference system, i.e., its rule base, is regenerated using the updated matrices M and O (Algorithm 3), and the process is repeated as long as new images are available.

IV. EXPERIMENTS AND RESULTS

This section describes the experiments conducted in order to test the proposed self-configuring EFIS (SC-EFIS). To build the initial fuzzy system, for each training set, a set of randomly selected images from the data set were used for the extraction of the features along with the optimum parameters as output. This initial fuzzy system was then used to test the proposed method using the remaining images. The initial fuzzy system evolves as long as new (unseen) images are fed into the system and as long as the segmentation results produced by the algorithms are corrected by an expert user in order to generate optimal parameter values. This process drives the evolution of the fuzzy rules for segmentation. We used a 10-fold leave-n-patients-out cross-validation for the experimentation. The results of ten different trials for each segmentation technique and for each parent algorithm are presented in order to validate the performance of SC-EFIS. The number of rules was monitored during the evolution process in order to acquire empirical knowledge about the convergence of the evolving process. The experimental results using an image dataset for global thresholding are presented.

A. Image Data

The target dataset was developed from **35 breast ultra**sound scans that were segmented by an image-processing expert with extensive experience in breast lesion segmentation (the second author). The images, collected from the Web, are of different dimensions, ranging from 230×390 to 580×760 pixels (Figure 3, images resized for sake of illustration). These are the same images used to introduce EFIS originally [1].

Ultrasound images are generally difficult to segment, primarily due to the presence of speckle noise and low level of local contrast. It should be noted that the segmentation of ultrasound actually does require a complete processing chain, (including proper preprocessing and post-processing steps). However, the purpose of using these images was solely to demonstrate that the accuracy of the segmentation can be increased with the application of SC-EFIS.

B. Evaluation Measures

Considering two segments S (generated by an algorithm) and G (the gold standard image manually created by an expert), we calculate the average of the Jaccard index J (area overlap) [16]:

$$J(S,G) = \frac{|S \cap G|}{|S \cup G|},\tag{1}$$

and its standard deviation σ_J . As well, the 95% confidence interval (CI) of the Jaccard index CI_J is calculated . Finally, we performed t-tests to validate the null hypothesis for comparing the results of a parent algorithm and its evolved version in order to establish whether any potential increase in accuracy is statistically significant. Ground-truth images Gwere created so that the objects of interest (i.e., lesions and tumours) could be labeled as white (1) and the background as black (0). All thresholding techniques were used consistently to label object pixels in this way as this was done in EFIS. We also calculate "Maximum Achievable Accuracy" (MAA) determined via exhaustive search and through comparison with gold standard images. MAA of each i hence the maximum accuracy that any global thresholding method can achieve.

C. Results

To compare with EFIS, the SC-EFIS results are calculated for global thresholding. The results are discussed with respect to rule evolution, and accuracy verification using the Jaccard results. As well, we compare the results of EFIS and SC-EFIS with other methods such as local thresholding by Niblick [4], the Huang/Wang method for fuzzy thresholding [5], the Kittler algorithm [6], the interval-based fuzzy thresholding according to Tizhoosh [7], [17] and the Otsu method. It should be noted that comparing with the Niblack method is actually not a correct comparison because it is a local method whereas all other methods operate globally, so it is expected that Niblack should generally outperform global methods.

Rule Evolution – Fig. 4 indicates the change in the number of rules during the evolving of the thresholding (THR) process. The initial number of rules increases with any incoming image and then begins to decrease as additional images become available. Accuracy Verification – Ten different trials/runs

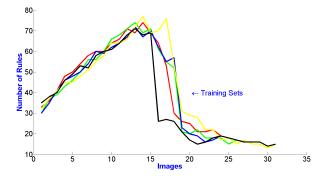


Fig. 4. Rule evolution for SC-EFIS for thresholding: The number of rules increases first as more images are processed but then drops and seems to converge toward a lower number of rules. Each curve shows the number of rules for a separate trial/run.

TABLE ICOMPARISON OF EFIS, SC-EFIS, AND 4 OTHER GLOBAL THRESHOLDINGTECHNIQUE AS WELL AS ONE LOCAL THRESHOLDING METHOD ([7], [17],[4], [6], [5]): AVERAGE AND STANDARD DEVIATION OF THE JACCARDINDEX $J \pm \sigma_J$ and 95% confidence interval CI_J .

Run	Method	$J \pm \sigma_J$	CI_J
1	MAA	79%±12%	[75% 84%]
	EFIS-THR	62%±25%	[53% 71%]
	SC-EFIS-THR	63%±23%	[54% 72%]
	Niblack (local)	56%±24%	[47% 65%]
	Huang	45%±27%	[35% 55%]
	Kittler	39%±32%	[27% 51%]
	Tizhoosh	$35\%{\pm}32\%$	[23% 47%]
	Otsu	$28\%{\pm}25\%$	[18% 37%]
2	MAA	79%±11%	[75% 83%]
	EFIS-THR	60%±24%	[51% 69%]
	SC-EFIS-THR	59%±26%	[49% 69%]
	Niblack (local)	$57\%{\pm}25\%$	[48% 66%]
	Huang	$44\%{\pm}29\%$	[34% 55%]
	Kittler	$41\%{\pm}31\%$	[29% 52%]
	Tizhoosh	$38\%{\pm}32\%$	[26% 50%]
	Otsu	$29\%{\pm}25\%$	[19% 38%]
3	MAA	79%±12%	[74% 83%]
	EFIS-THR	63%±23%	[54% 71%]
	SC-EFIS-THR	$65\%{\pm}21\%$	[57% 73%]
	Niblack (local)	$59\%{\pm}24\%$	[49% 68%]
	Huang	$46\%{\pm}27\%$	[35% 56%]
	Kittler	41%±33%	[29% 53%]
	Tizhoosh	$35\%{\pm}33\%$	[23% 48%]
	Otsu	$28\%{\pm}23\%$	[20% 37%]

are presented for each method. Each run is an independent experiment involving different training and testing images. Table I enables a comparison of EFIS and SC-EFIS results for global thresholding with different global and local thresholding techniques. It is clear that, in the three experiments, EFIS and SC-EFIS provide outcomes that are more accurate than those produced with the non-evolutionary thresholding techniques. As well, if the results for SC-EFIS are sightly lower than EFIS (e.g. in the 2nd run, Table I), it is statistically significant. Besides one should be keep in mind that SC-EFIS does not have EFIS limitations.

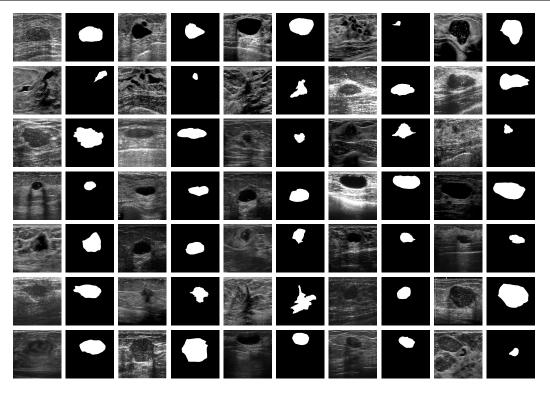


Fig. 3. Breast ultrasound scans used in our experiments. All images were segmented by an image-processing expert.

V. CONCLUSIONS

Evolving fuzzy image segmentation (EFIS) has been recently proposed to provide evolving and user-oriented adjustment. EFIS is a generic segmentation scheme that relies on user feedback in order to improve the quality of segmentation. Its evolving nature makes this approach attractive for applications that incorporate high-quality user feedback, such as in medical image analysis.

However, EFIS entails some limitations, such as parameters that must be selected prior to the running of the algorithm and the lack of an automated feature selection component. These drawbacks restrict the use of EFIS to specific categories of images. An improved version of EFIS, called self-configuring EFIS (SC-EFIS) was proposed in this paper. SC-EFIS is a generic image segmentation scheme that does not require setting of most parameters, such as number of features or detecting a region of interest. SC-EFIS operates with the data available and extracts major parameters necessary for its operation from those data. A comparison of the SC-EFIS results with those obtained with EFIS demonstrates the comparable accuracy of both schemes with SC-EFIS offering a much higher level of automation.

REFERENCES

- A. Othman, H. R. Tizhoosh, and F. Khalvati, "EFIS: Evolving fuzzy image segmentation," *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 1, pp. 72–82, 2014.
- [2] A. Othman and H. Tizhoosh, "Evolving fuzzy image segmentation," in IEEE International Conference on Fuzzy Systems (FUZZ), pp. 1603– 1609, 2011.
- [3] S. Warfield, "Simultaneous truth and performance level estimation (STAPLE): an algorithm for the validation of image segmentation," *IEEE Transactions on Medical Imaging*, vol. 23(7), pp. 903–921, 2004.

- [4] W. Niblack, An Introduction to Digital Image Processing. Birkeroed, Denmark: Strandberg Publishing Company, 1986.
- [5] L. Huang and M. Wang, "Image thresholding by minimizing the measure of fuzziness," *Pattern Recognition*, vol. 28, pp. 41–51, 1995.
- [6] J. Kittler and J. Illingworth, "Minimum error thresholding," Pattern Recognition, no. 19, pp. 41–47, 1986.
- [7] H. Tizhoosh, "Image thresholding using type II fuzzy sets," Pattern Recognition, vol. 38, no. 12, pp. 2363–2372, 2005.
- [8] S. Rahnamayan and H. Tizhoosh, "Image thresholding using micro opposition-based differential evolution (micro-ODE)," in *IEEE World Congress on Evolutionary Computation*, pp. 1409–1416, 2008.
- [9] M. Shokri and H. Tizhoosh, "Using reinforcement learning for image thresholding," in *Canadian Conference on Electrical and Computer Engineering*, pp. 1231–1234, 2003.
- [10] H. Tizhoosh and F. Sahba, "Quasi-global oppositional fuzzy thresholding," in *IEEE International Conference on Fuzzy Systems*, pp. 1346– 1351, 2009.
- [11] P. Mitra, C. Murthy, and S. K. Pal, "Unsupervised feature selection using feature similarity," *IEEE transactions on pattern analysis and machine intelligence*, vol. 24, no. 3, pp. 301–312, 2002.
- [12] X. He, D. Cai, and P. Niyogi, "Laplacian score for feature selection," *Advances in Neural Information Processing Systems*, vol. 18, p. 507, 2006.
- [13] Z. Zhao and H. Liu, "Spectral feature selection for supervised and unsupervised learning," in *Proceedings of the 24th international conference* on Machine learning, pp. 1151–1157, ACM, 2007.
- [14] D. Cai, C. Zhang, and X. He, "Unsupervised feature selection for multicluster data," in *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 333–342, ACM, 2010.
- [15] A. K. Farahat, A. Ghodsi, and M. S. Kamel, "Efficient greedy feature selection for unsupervised learning," *Knowledge and Information Systems*, pp. 1–26, 2012.
- [16] K. V. Tan P.-N., Steinbach M., Introduction to Data Mining. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 2005.
- [17] H. Tizhoosh, "Type II fuzzy image segmentation," in Fuzzy Sets and Their Extensions: Representation, Aggregation and Models Studies in Fuzziness and Soft Computing, vol. 220, pp. 607–619, 2008.