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Multiobjective Evolutionary Optimization for Tumor Segmentation of Breast Ultrasound Images

Ye-Hoon Kim, Baek Hwan Cho, Yeong Kyeong Seong, Moon Ho Park, Junghoe Kim, Sinsang Yu, and Kyoung-Gu Woo

Abstract— **This paper proposes a robust multiobjective evolutionary algorithm (MOEA) to optimize parameters of tumor segmentation for ultrasound breast images. The proposed algorithm employs efficient schemes for reinforcing proximity to Pareto-optimal and diversity of solutions. They are designed to solve multiobjective problems for segmentation accuracy and speed. First objective is evaluated by difference between the segmented outline and ground truth. Second objective is evaluated by elapsed time during segmentation process. The experimental results show the effectiveness of the proposed algorithm compared with conventional MOEA from the viewpoint of proximity to the Pareto-optimal front (improved by 16.4% and 12.4%). Moreover, segmentation results of proposed algorithm describe faster segmentation speed (1.97 second) and higher accuracy (8% Jaccard).**

I. Introduction

Computer-aided detection/diagnosis (CAD) supports a clinical decision to provide second opinion to radiologist from medical images such as X-ray, CT, ultrasound images. It extracts contour of lesion by finding an outline pixel of object in the image. In other words, CAD system contains segmentation module for outline detecting of suspicious lesion. The radiologist extracts precise features and diagnose more correctly as the segmentation of tumor is more accurate.

There have been conventional researches on image segmentation [1]–[3]. Active contour model is one of the representative segmentation algorithm [1]. Basically, active contour model searches the outline iteratively which has the largest difference of intensity between inside and outside. Level set algorithm has shown robust performance as a representative segmentation technique even though edge of lesion was not clear [2], [3]. It expends outline iteratively until it finds the outline satisfying energy function is zero.

The performance of the level set algorithm depends on several parameters of the energy function including global (local) energy term, smoothness term and edge term [4]–[6]. Usually, the parameters which are robust to image data set of large scale have been adjusted by developer with time consuming. Thus, automatic parameter optimization skill is required such as evolutionary algorithms [7]–[11].

The segmentation algorithms should satisfy higher accuracy. Segmentation speed is an another consideration since radiologist has to deal with a lot of medical images of patients per day. Also, processing time of each slice for 3D volume data is important factor. Thus, the aim of optimizing segmentation algorithm in medical image is that it should segment the outline of tumor accurately and find it as soon as possible. The difference of segmented lesion compared with ground truth should be minimized for former objective, whereas elapsed time during the segmentation should be minimized for the latter objective. There was a research for multiobjective image segmentation using quantum-inspired evolutionary algorithm [12]. The authors considered two objectives: intra-region homogeneity and inter-region heterogeneity. They focused on split/merge strategy using clustering algorithm however they did not consider speed for segmentation.

Multiobjective evolutionary algorithm (MOEA) can solve these problems efficiently by utilizing a concept of Pareto-optimal solution. The growing interest in highly complex real-world problems has motivated the growth of MOEAs [13], [14]. The nondominated sorting genetic algorithm (NSGA) was proposed [13] and improved as NSGA2, which is a strong elitist method with maintaining diversity efficiently using nondominated sorting and crowding distance [14].

This paper proposes reinforcing proximity evolutionary algorithm (RPEA) for optimizing tumor segmentation of ultrasound breast images. It includes new metrics to enhance traditional ranking and measuring diversity of the solutions in population. First metric makes evolution process focus on the proximity to the Pareto-optimal front and second metric measures density of solutions. Proposed two metrics can compare the superiority of each solution for sorting and overcome the weakness of traditional algorithms. Moreover, two-objective functions in terms of accuracy and speed are designed in the paper. The obtained solutions by proposed algorithm are verified through plotting the solutions in objective space and showing segmented images examples.

This paper is organized as follows. Section II presents schemes of proposed algorithm. Section III describes experimental environment such as the ultrasound data acquisition, target parameter for optimization, definition of fitness functions and parameters for MOEA. In Section IV, experimental results demonstrate the effectiveness of proposed algorithm and various cases according to obtained parameter setting. Finally, concluding remarks follow in Section V.

The authors are with Data Analytics Group, SAIT, Samsung Electronics, Yongin, 446–712, Republic of Korea. (phone: 82-31-280-9856; fax: 82-31-280-9860; email:{yehoon.kim, baekhwan.cho, yk.seong, moonh.park, kjh94, sinsang.yu, kg.woo}@samsung.com).

II. Proposed Algorithm

In the real-world, user tends to select solutions satisfying multiobjectives (accuracy and speed) simultaneously [17]. In other words, the radiologist avoids to use too inaccurate or slow segmentation processor. Therefore, proposed scheme in this section reinforces the proximity to Pareto-optimal front by disregarding extreme solutions.

A. Reinforcing Proximity

Most MOEAs rank or sort the solutions according to domination relation. Solution A and B in Fig. 1 are indifferent by definition of domination. In other words, they are neither dominated nor dominate each other. No solution is better theoretically, however solution A is much valuable than solution B in real-world application. The reason is that first fitness value (f_1) of solution A is much better than that of solution B while second fitness value (f_2) of solution A and B are similar relatively. In this case, user will select solution A and it is closer to the origin. In order to deal with this case, proximity metric $\boldsymbol{\mathcal{P}}$ to distinguish better solution is proposed as follows:

$$\boldsymbol{\mathcal{P}}_A(A,B) = \sum_{k=1}^{N} \frac{(f_k^A - f_k^B)}{1+(f_k^A + f_k^B)} \tag{1}$$

where N is the number of objectives. f_k^A and f_k^B are k^{th} objective values of solution A and B. It measures related distance between two solutions. The smaller $\boldsymbol{\mathcal{P}}_A$ is better for minimization problem and vice versa.

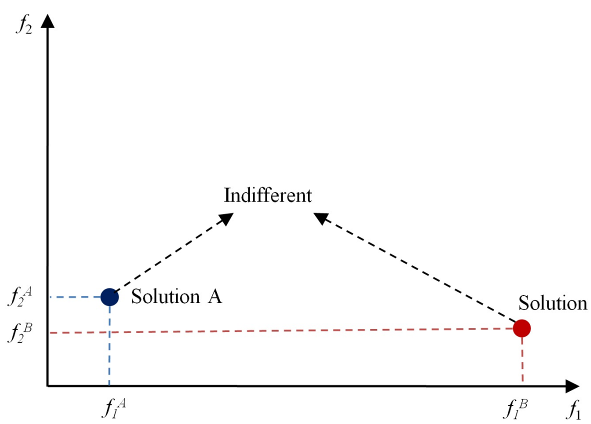

Fig. 1. Comparison of indifferent solutions for reinforcing proximity.

B. Enhanced Diversity Metric

Conventional diversity metric of solutions (e.g. cuboid distance [14]) could not differentiate more diverse solution in particular cases. It refers distance in the vicinity of the solution (in intra-cluster) however distance between inter-clusters was not considered. For instance, solution C and D have same cuboid distance however solution D is much valuable than C from the unique viewpoint. In other words, the solution in the least crowded area is the best. Thus, diversity metric to distinguish such case using Euclidean distance between every solution is proposed. Following metric $\boldsymbol{\mathcal{D}}$ can recognize that the solution D has better diversity than C because neighbors in the vicinity of the solution D are less crowded than C.

$$\boldsymbol{\mathcal{D}}_i = \sum_{j=1}^{n} \sqrt{\sum_{k=1}^{N} (f_k^i - f_k^j)^2} \tag{2}$$

where n is the number of solutions in a population. f_k^i is k^{th} objective value of i^{th} solution.

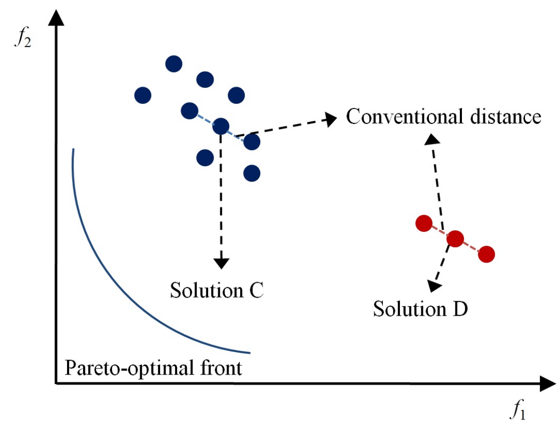

Fig. 2. Comparison of solutions to overcome the limitation of conventional diveristy metric.

C. Procedure of proposed algorithm

This paper proposes reinforcing proximity evolutionary algorithm (RPEA) to enhance proximity of solutions to Pareto-optimal front with preserving the diversity. Fig. 3 shows the whole procedure of RPEA. Each step is described in detail as follows.

Procedure RPEA
Begin
i) Initialize parent population of size n
ii) **while** (**not** termination condition) **do**
    begin
iii)   Make offspring population by perturbation
iv)   Evaluate solutions in merged population of parent and offspring
v)   Sort merged population based on $\boldsymbol{\mathcal{P}}$ and $\boldsymbol{\mathcal{D}}$
vi)   Select top n solutions as a parent
    end
end

Fig. 3. Procedure of RPEA.

i) Parent population is initialized randomly.

ii) Until the termination condition is satisfied, it runs in the while loop. The termination criterion is maximum number of generations.

iii) Perturbation techniques such as crossover and mutation to make offspring solutions are applied.

iv) $2n$ population is created by merging parent and offspring population and evaluated.

v) The merged population is sorted by proposed two metrics. For multiobjective minimization problem, the solution with negative and smaller $\mathcal{P}$ is better for first comparison criterion. If the solutions are similar ($0 < \mathcal{P} < \epsilon$), the solution with larger $\mathcal{D}$ is better for second comparison criterion. ϵ means threshold for similarity tolerance of each solution and it adjusts preserving the diversity at evolution process.

vi) Only top n solutions are survived as parent solutions in the next generation to inherit better characteristics of solutions.

III. Experimental Environment

A. Ultrasound Breast Images

Pool of ultrasound breast images have 5,252 breast tumor images from the Samsung Medical Center, Seoul, South Korea between 2006 and 2011. The mean age of benign/malignant cases was 45/49 years, and the age range was from 11/24 to 81/86 years. 2,757 benign and 2,495 malignant cases were considered. Images were generated by using a Philips ATL iU22 ultrasound machine and the size of each image was 1024 $\times$ 768 pixels with a spatial resolution of 0.23 mm/pixel.

B. Target Parameters and Fitness Evaluation

The region-based active contour model with point classification which is one of the recent segmentation algorithm was used for fitness evaluation [18]. Parameters (the number of maximum iterations, α, β, $\lambda(=\lambda_1=\lambda_2)$) of energy function defined in eq. (11) in [18] were optimized by proposed algorithm. The equation consists of global, local and smooth term without edge term.

Two objective functions for fitness evaluation are defined as follows:

$$f_1 = 1 - Jaccard\ (error\ rate) \quad (3)$$

$$f_2 = Elapsed\ time\ (speed) \quad (4)$$

The error rate for accuracy was measured by Jaccard which is the ratio of intersection with union of segment result of pixel with the ground truth. Segmentation speed was measured by elapsed time during the segmentation process. Each objective value was averaged per each image.

C. Parameters for MOEA

Population size was 10 and the number of generations was 20 for NSGA2 and proposed RPEA. Adaptive mutation for real number was used with dynamic mutation probability. The mutation probability was decreased from 0.2 to 0.1 according to generation increase. Threshold for similarity tolerance (ϵ) was 0.5. 10 ultrasound images which were randomly selected in breast tumor image pool were used to optimize the parameters since a lot of images need plenty of time to evaluate the fitness. Tests were run on a personal computer with Intel core i5, 2.67GHz CPU and 4GB memory. Seed ellipse indicating tumor detection were described by radiologists.

IV. Results

As a results, the solutions of RPEA were closer to Pareto-optimal front than those of NSGA2 as described in Fig. 4. Solution 3 of RPEA improved the performance as higher as 16.40% and 12.40% than Solution 1 and 2 of NSGA2 in terms of proposed metric $\mathcal{P}$, respectively. It means proposed RPEA found better solutions by reinforcing the proximity from the point of view of accuracy and speed for segmentation at the same time.

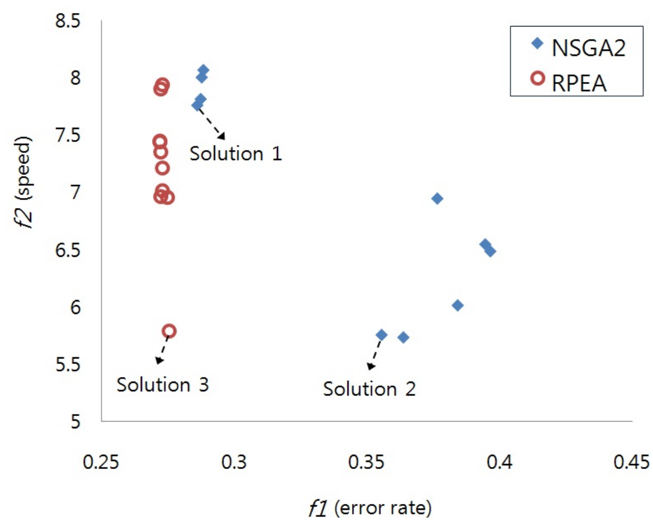

Fig. 4. Obtained solutions from NSGA2 (including solution 1 and 2) and RPEA (including solution 3).

Segmentation results of solution 1 which focused on the accuracy, solution 2 which focused on the speed and solution 3 which optimized both are shown in Table I and Fig. 5. User could select any parameter setting of obtained solutions for segmentation as his/her preference. For instance, more accurate segmentation processor will help beginners and the faster one will be useful for experts. Solution 3 from proposed RPEA applied to second breast image as shown in Fig. 6 was obtained with better performance in terms of speed (f_2) compared with solution 1 and accuracy (f_1) compared with solution 2. For instance, solution 1 and 3 described similar outline of tumor however solution 3 was much faster than solution 1 (1.97 second on average) and more accurate than solution 2 (8% Jaccard) as shown in Table I. Therefore, user would select the parameter setting of solutions by using proposed RPEA rather than NSGA2 which are much valuable for user in real-world applications.

V. Conclusions

In this paper an evolutionary multiobjective optimization (EMO) technique was employed to find set of optimized parameters for ultrasound image segmentation, which were satisfying two objectives at the same time. As a novel EMO,

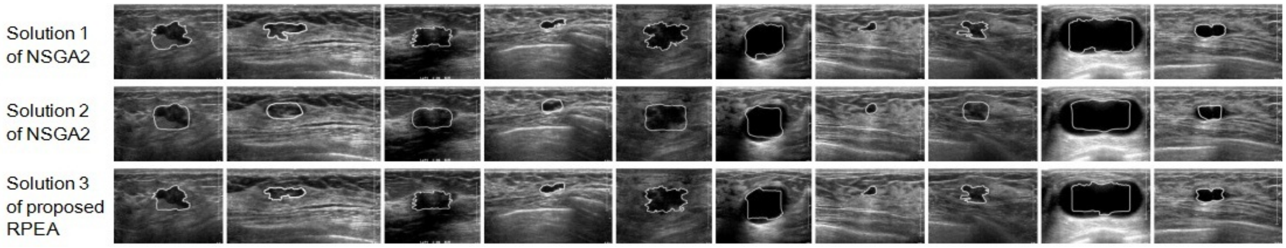

Fig. 5. Segmentation results of ultrasound breast images obtained from NSGA2 and RPEA.

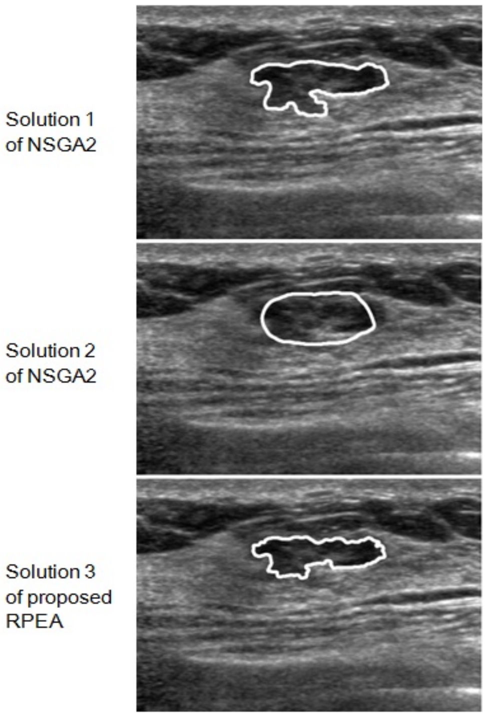

Fig. 6. Segmentation results for second breast image in Fig 5.

TABLE I
OBJECTIVE VALUES OF SOLUTIONS OBTAINED BY NSGA2 AND RPEA.

	1-Jaccard (f_1)	Elapsed time (f_2)
Solution 1 (NSGA2)	0.2861	7.7611
Solution 2 (NSGA2)	0.3556	5.7596
Solution 3 (RPEA)	0.2756	5.7906

the reinforcing proximity evolutionary algorithm (RPEA) was proposed to find out efficient parameter sets of active contour model. The proposed RPEA was based on strengthened proximity to the Pareto-optimal front and calculation of distance between the entire solutions. For the performance evaluation, RPEA was applied to the tumor segmentation problem of ultrasound breast images. As a results, RPEA generated more practical solutions with better proximity to Pareto-optimal front than the conventional algorithm. Moreover, various parameter settings optimized were compared in terms of describing ability of tumor lesion and processing time. After feasibility validation in this paper, additional medical images and objectives will be considered as a future work.

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