AUTOMATIC SEGMENTATION OF SKIN LESION IMAGES USING EVOLUTIONARY STRATEGY

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ABSTRACT

Malignant melanoma has a good prognosis if treated early. Accurate skin lesion segmentation from the background skin is important not only because the shape feature can be directly derived from the process, but also because it can provide a scope for texture analysis. In this paper, we propose an evolutionary strategy based segmentation algorithm to identify the lesion area by an ellipse. It can detect the lesion automatically without setting parameters manually. The method is validated by experiments and comparisons with manually segmentation by an expert and algorithms developed in [1, 2].

Index Terms— Evolutionary Strategy, image segmentation, biomedical application, fitness function, skin lesion

1. INTRODUCTION

Early detection of cancerous skin lesion has been agreed to be very important due to the wide spread of skin cancer as well as the economic and successful treatment if detected early. Malignant melanomas, the deadliest form of all skin cancers, has cure rate of higher than 95% when detected at an early stage[3]. Segmentation is essential in systems classifying malignant and benign cases. Zouridakis, et al. [1, 2] developed an automatic system to determine the malignancy based on the size difference in skin lesion images from two imaging modalities: Cross-polarization Epiluminescence Microscopy (XLM) and Transillumination Epiluminescence Microscopy (TLM). The main components of the system are the segmentation of the lesion area from the background by four algorithms: sigmoid, PCT, PCT+sigmoid, and fuzzy c-mean. A scoring system then selects the best segmentation result. It has a a satisfactory performance with error rate less than 15% compared to manually segmentation by an expert. But for some other images, all the four algorithms give very poor performance(error rate higher than 40%). So, it is still worthy to try other segmentation algorithms for this problem.

In this paper, we propose to use Evolutionary Strategy(ES) for skin lesion image segmentation. ES has the property of seeking global optimum and getting out of local optimum automatically. Yuan et al. [4] applied ES to feature identification in natural and synthesis of images with multiple features. To apply the ES algorithm to skin lesion image segmentation, we formulated the segmentation problem as a search problem similar to [4]. The lesion area is segmented by an ellipsoid, whose parameters are optimized by ES algorithm with respect to the defined objective function. The method is validated by experiments on the same data set as used in [1, 2]. The experiments show ES based algorithm has a better performance than the algorithms in [1, 2].

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2. RELEVANT WORKS

Zouridakis, et al [1, 2] proposed an automatic skin lesion malignance detection system based on size difference of XLM image and TLM image. The XLM imaging modality captures only surface pigmentation, while the TLM imaging modality can visualize both surface pigmentation and the increased blood volume and vasculature around a lesion if present. Based on skin physiology, when there're cancerous lesion being developed, more vascular activity can be observed, resulting in bigger lesion area for TLM images than that of XLM images [1, 2]. Each image undergoes some preprocessing procedures including masking, cropping, color converting and hair removal. After that, four segmentation techniques are employed to identify the lesion area: sigmoid, PCT, PCT+sigmoind, and fuzzy c-means. The segmentation results of these techniques are then selected by a scoring system, and the boundary of the selected one will be smoothed.

The performance of the malignancy detection system relies on these four segmentation methods. However, these four segmentation methods all have their own limitations when dealing with skin lesion images. The sigmoid method may fail if the histogram of the red channel can not be fitted by two Gaussian curves. The PCT is not based on any statistic property, and in some cases it can not generate enough contrast between the lesion and the background. The combined sigmoid and PCT produces better result, but it still suffer from the same problem as applying PCT independently. Moreover, the threshold determined by this method is easily influenced by some artifacts. The fuzzy c-mean can generally produce good performance for most image pairs. However, its performance is very poor. This introduces a lot of uncertainty when comparing the area size for TLM and XLM images. A scoring system is designed to overcome the limitation of different segmentation methods by selecting the best segmentation based on majority vote mechanism. It looks at the difference between segmentation results and the edge strength and select the one that agrees with majority while having the best edge strength.

To improve the performance and the robustness of the system, we developed an ES-based segmentation algorithm. Because of the inherent properties of ES algorithm, the ES-based segmentation algorithm has three distinct characteristics when applying to skin lesion images: (1)It is an unsupervised segmentation algorithm whose performance does not depend on initialization; (2)its segmentation results are not easily affected by artifacts in the image; (3)it is based on the statistical property of the image.

Because of these properties, images fed into the ES-based segmentation algorithm do not need to go through the full preprocessing steps mentioned above. In specific, ES-based segmentation method does not need hair removal procedure. In addition, ES-based method is very robust to the initial points selected, in contrast to the GVF snake methods [5].

Evolutionary Strategy (ES) is one kind of evolutionary computation that has been applied to various optimization problems. Genetic Algorithm(GA), another evolutionary computation technique, is the most popular and has already been used in the area of image segmentation [6, 7] and in the specific area of medical image segmentation[8, 9]. The major difference between GA and ES is that the gene in GA is encoding in string consisted of 0 and 1 while ES gene evolves in the domain of real number. Because the gray levels of skin lesion images are real number, we used ES rather than GA to avoid information loss in the representation. Yuan et al. [4] applied ES successfully to feature identification of natural and artificial images. To apply the ES algorithm to skin lesion image segmentation, we formulated the segmentation problem as a search problem similar to [4]. The lesion area is segmented by an ellipsoid, whose parameters are optimized by ES algorithm with respect to the defined objective function. In this paper, we also use an ellipsoid to segment the lesion within skin images. However, we designed a different objective function for lesion segmentation.

The main reason we chose to use an elliptic template for segmentation is because an ellipsoid can be fully defined by five parameters. This makes it easy to implement an ellipsoid region based objective function. Another reason is that the constraints on the shape of the segmentation contour will make the algorithm more robust [10, 11]. In addition, to provide a scope for texture, a regular shape is preferred.

The active contour method, such as the GVF snake algorithm [5] has been shown to be a promising method in skin lesion image segmentation in [12]. Chan proposed a region-based active contour algorithm, referred to as ”active contour without edges” [13], which is more robust on the initial condition. We adopted the region-based scheme similar to that of the active contour without edges [13] to design our objective function for it is not sensitive to initial condition and robust to noise.

3. ES ALGORITHM OVERVIEW

Evolutionary Strategy (ES) is a random search based optimization technique. We chose ES as our optimization methods because of its two properties. First of all, like other evolutionary computation methods, ES algorithm will not stop at local optimum, but will converge to global optimum. Secondly, ES is formulated for optimization of real number functions.

The basic elements for using ES include: (1) A population (more than one) of candidate solutions; (2) A measure over each member of the population (or candidate solution) referred to as fitness/objective function; (3) A ’SELECTION” operator that differentiates between members of a population based on the fitness value; (4) A ”MUTATION” operator that makes random changes to a member of the population (corresponding to asexual reproduction in biology evolution); (5) A ”RECOMBINATION” operator that generates a new organism (or individual solution) by combining ”genetic material” from random selected members of the population. Fig.1 shows the evolution of candidate solutions (i.e., organisms) in one ES generation. The gene pool stores the candidate so-

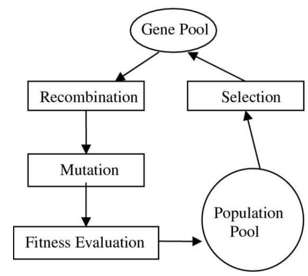

Fig. 1. Flowchart of ES

lutions selected from population pool (μ). They are used as parents to generate chromosomes of the next generation. A next generation of λ organisms (offspring) is generated using organism from the gene pool (parents gene) by undergoing recombination and mutation operations. The fitness of a newly generated offspring is evaluated using the user defined fitness/objective function. The offspring are then added to the population pool and then the selection rules are applied to select the best candidates for the succeeding gene pool. This finishes one loop of one generation of the ES algorithm which is summarized in Fig.1.

4. APPLY ES TO SEGMENT SKIN LESION IMAGE

We formulated the segmentation problem into a numerical optimization problem by defining an ellipsoid structure that enclose the target segmentation. We can use five parameters, (X, Y, a, b, θ), to define an ellipsoid structure. We used them as the objective variables of an ES organism(candidate solution), such as $(X, Y, a, b, \theta; \delta_1, \delta_2, \dots, \delta_5; \gamma_1, \gamma_2, \dots, \gamma_{10})$, where the object variables are defined as:

- (X, Y): the center of an ellipse;
- (a, b): the minor and major axis radius of an ellipse;
- θ: the rotation angle of an ellipse.

The control variables, $\overrightarrow{\delta}$ and $\overrightarrow{\gamma}$, have the standard interpretation of defining the hyper-ellipsoid that proscribes the mutation operator.

The objective function returns the fitness value of an ES candidate solution. The region-based objective function we designed as defined in Equation (1) is according to the property of skin lesion images. That is, the lesion and the background skin is different.

$$F(X, Y, a, b, \theta) = \int_{\omega} |I(x,y) - c_1|^2 dxdy + \int_{\Omega \setminus \bar{\omega}} |I(x,y) - c_2|^2 dxdy \quad (1)$$

where $I(x, y)$ is the intensity value of the coordinate (x, y); ω is the area enclosed by the ellipse defined by (X, Y, a, b, θ); Ω is the area of the pixels whose intensity value is not zero (because we used mask to get rid of rings in the pre-processing step, there exists black area with intensity value zero in the images that will distract the search process.); c_1 and c_2 represent the average intensity value of the pixels inside and outside ω respectively. Such an objective function favors an ellipse dividing the image into two homogenous areas with minimum variation in both regions respectively.

The initial ellipse can be either inside the lesion area, or in the middle of the image. Our experiment results show that ES guarantees similar performance for different initial center points and ellipsoid size. This demonstrates the robustness of ES algorithm to the initialization. We adopted CMAES [14] to perform ES optimization. The CMAES enables us to specify a search area to further improve computational efficiency. We put the constraints that $5 < a, b < 120$, and $1/9 \times N < X, Y < 8/9 \times N$, where N is the size of the image. These constraints are designed based on the fact that all lesion areas should not exceed the scope of the image, and always occupy significant amount of areas near the center of the image if not all. The fitness function of each individual is the same as Eq.(1). The population size and the parent number of ES are set to be 8 and 4 respectively.

The segmentation procedure can be illustrated by Fig.2. The first step is preprocessing which is similar to [1, 2]. The second step is applying ES to minimize Eq.(1) on the preprocessed image. For XLM image, we apply ES one time and then output the segmented region inside the ellipse for the third step. For TLM image, we apply ES two times. The result from the second step is already good enough for most images. But for some images whose lesions are very small, we still need to apply ES one more time to get a satisfactory result. In the third step, we first detect the peaks of the smoothed histogram of the image output by step two. Because lesion area always has lower intensity, the first peak of the histogram will represent the lesion area. If the first peak is lower than the maximum peak, it means that lesion area is not the dominant feature inside the ellipse. In that case, we need to apply ES one more time. Otherwise, we just output the result of step two.

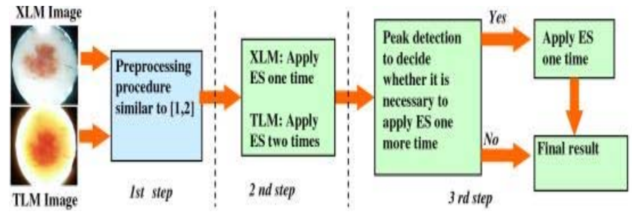

Fig. 2. Framework for the segmentation procedure

5. EXPERIMENTS AND RESULTS

We applied the ES-based algorithm to the same skin lesion image sets used in [1, 2]. Among the 68 pairs of XLM and TLM images, only 51 XLM images and 60 TLM images were manually segmented by dermatologist since other images do not show pigmentation [2]. These are treated as true values, and we validate our ES based segmentation algorithm by comparing our results with the manually segmented results.

Comparing with other four segmentation methods presented in [1, 2], the experiment results show that ES-based segmentation method performs better and is more robust under various imaging conditions. For most of the 111 skin lesion images, where the edge is well defined and the noise is low, our method achieves as good segmentation as those achieved by four segmentation methods with the scoring system [1, 2]. Fig.3 presents segmentation results where ES performs much better than previous methods. In Fig.3, each row shows the segmentation results from three methods for one image. The first column shows the results from the ES based algorithm. The middle column shows manual segmentation by a certified dermatologist. We use the manual segmentation results as the true values in this paper. The last column shows the segmentation results for the same image from the scoring system in [1, 2].

Results shown in Fig.3 demonstrate better segmentation results from ES-based algorithm for Lesion 38(TLM), 35(TLM), and 13(XLM). The edge of the lesion 38 is very vague; the lesion 30 is very small; and lesion 13 is lesion clusters with holes in between. Based on the objective function in Eq.(1),

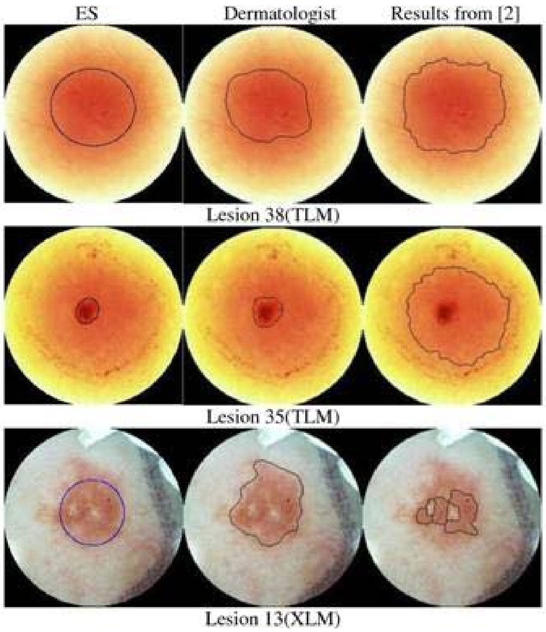

Fig. 3. Comparing ES, dermatologist , and [2]'s results.

our algorithm is not affected by the edge strength (lesion 38), size of the lesion versus homogeneous skin texture (lesion 35), and holes in the middle of the lesion (lesion 13). In specific, under close examination, for lesion 35, the proposed ES-based methods can identify smaller region than the algorithms in [1, 2]. This is because we incorporated more detailed region information using three-step procedure as described in Section 4. In summary, ES based segmentation algorithm is more robust and cannot be easily affected by artifacts.

6. DISCUSSION AND CONCLUSION

In this paper, we present an ES-based segmentation method developed for automatic skin lesion images segmentation. Experiments were done for 60 TLM and 51 XLM images. Results demonstrate that our ES-based algorithm is more robust and cannot be easily affected by artifacts. Another advantage of the algorithm is that it does not require any user input parameters, realizing total automation in skin lesion segmentation. Our ES-based segmentation method is flexible to adopt other fitness function. In the future, we plan to incorporate some edge and texture information to further improve the segmentation results.

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