Algorithms for Histopathology Image Detection and Segmentation

Subjects: Computer Science, Artificial Intelligence

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Histopathology image analysis is considered as a gold standard for the early diagnosis of serious diseases such as cancer. The advancements in the field of computer-aided diagnosis (CAD) have led to the development of several algorithms for accurately segmenting histopathology images.

nature-inspired algorithms particle swarm optimization multiobjective algorithms image segmentation thresholding histopathology

1. Introduction

Histopathology is a branch of biology which deals with the examination of diseased tissues under a microscope to diagnose diseases [1]. Histopathology is useful in diagnosing cancerous conditions, identifying the stage of cancer and other inflammatory diseases. Though histopathology image analysis by pathologists plays a critical role in the early diagnosis of cancer, analysing a huge amount of tissue images under a microscope is a tedious and time-consuming task. This could further be hindered due to ambiguous regions in the histopathology images, inaccuracies in the devices, and human error. In recent times, digital pathology coupled with advancements in computer-aided diagnosis (CAD) systems is revolutionizing the area of histopathology. CAD systems are automated image analysis systems that can assist medical practitioners. Detection and segmentation of regions of interest (ROIs) from whole-slide images (WSIs) are some of the core operations of CAD systems in histopathology image analysis.

The literature contains a variety of histopathology image segmentation techniques, including traditional methods as well as deep learning methods used in CAD systems [2]. Traditional image processing methods, such as thresholding, region growing, clustering, watershed, active contour models, neural networks, and wavelet transforms, have been widely used for histopathology image segmentation [3][4][5]. Recently, deep learning algorithms have exhibited their capacity to capture essential features for efficient image segmentation; however, the performance of deep learning models is heavily dependent on the quality and quantity of training data and the amount of training time. The lack of huge annotated histopathology image data is a major challenge in applying deep learning models for histopathology image segmentation [4].

Thresholding is a simple and effective traditional image segmentation technique. In thresholding, an input image is divided into multiple images containing various regions based on threshold values. In multilevel thresholding, k

threshold values are used to divide the image into k+1 images with several distinct regions. The optimal threshold is the best intensity value that segments the ROIs from the image accurately. Traditionally, the optimal threshold is identified by applying each intensity value of the image as a threshold value and then comparing the segmentation result. Thus, identifying the optimal threshold value is a complex and time-intensive task.

Another effective method widely used in the literature is to treat the problem of finding the optimal thresholds as an optimization problem and solve it using nature-inspired optimization algorithms. If the optimization problem uses single objective function it is called as a single-objective optimization problem (SOP). An optimization problem with more than one objective function is called a multiobjective optimization problem (MOP) [6][7][8]. The particle swarm optimization (PSO) algorithm is a nature-inspired optimization algorithm. It was developed by Kennedy and Eberhart (1995) [9], inspired from the natural behaviour of flocks of birds and schools of fish. PSO is a population-based stochastic algorithm used to solve SOPs based on the intelligent, coordinated movement of a swarm of particles. Multiobjective particle swarm optimization (MOPSO) is a variant of the PSO algorithm which is used to solve MOPs [10][11]. MOPSO has several advantages over PSO, including its ability to optimize multiple objectives, maintain diversity in the population, achieve better convergence to the true Pareto-optimal front, provide a range of solutions that represent the trade-off between the conflicting objectives, and being easy to implement. Moreover, the optimization accuracy of MOPSO is comparatively higher than a single-objective PSO.

2. Image Segmentation Using PSO and Its Variants

PSO is a population-based stochastic optimization algorithm that has been widely used for solving various optimization problems. In the context of image segmentation, PSO has been applied to find the optimal threshold values for segmentation. Various modifications to PSO have been proposed to improve its performance for image segmentation, such as Darwinian particle swarm optimization (DPSO) and fractional order Darwinian particle swarm optimization (FODPSO).

Jothi and Rajam [12] proposed a PSO-based Otsu's multilevel thresholding method for the automatic segmentation of nuclei from the UCSB bio-segmentation dataset. Otsu's thresholding was considered as an optimization problem. Precision, recall, and F-measure were used as the evaluation metrics, all of which had high values for the dataset. Liu et al. [13] proposed a PSO-based image clustering approach with intra-cluster distance as an optimization function. Breast cancer histopathology images with magnification levels 40×, 100×, 200×, and 400× were used for checking the effectiveness of the proposed approach. The experimental analysis showed that PSO performed better than the genetic algorithm (GA) and K-means.

A number of studies have been carried out using PSO for the segmentation of images in other fields. Chakraborty et al. [14] developed an improved PSO-based multilevel thresholding to identify the optimal thresholds. This algorithm was tested on some grayscale images and medical images other than histopathology images. It was found to provide better fitness value and lesser CPU time when compared to existing algorithms, such as modified artificial bee colony, cuckoo search, firefly, PSO, and GA. Another improved image segmentation method based on dynamic particle swarm optimization was proposed by Li et al. [15]. This algorithm was applied to a large set of real crystal growth images. The experimental results showed that the proposed algorithm can successfully separate the texture of crystal growth images and provide high robustness. A PSO-based multilevel thresholding using Kapur's and Tsallis entropy was explored by Saini et al. [16]. This method was applied to normal brain magnetic resonance imaging (MRI). From the analysis, it was observed that Tsallis entropy worked more efficiently for the segmentation of cerebro spinal fluid and white matter regions when compared to Kapur's entropy. Peng et al. [17] proposed an improved PSO-Fuzzy C-means (PSO-FCM) algorithm for the segmentation of images obtained from a standard image dataset. Experimental results showed that this clustering segmentation algorithm provides better accuracy and noise resistance.

DPSO and FODPSO are two variants of the PSO algorithm which have been used in the following studies for image segmentation. Suresh and Lal [18] proposed an improved variant of the DPSO algorithm based on chaotic functions to improve the convergence rate of DPSO and the segmentation quality of satellite images. The effectiveness of the model was compared with other optimization algorithms, such as cuckoo search, harmony search, differential evolution, and PSO. It was found that the algorithm suffered from higher computational complexity than the other algorithms. Tang et al. [19] applied the FODPSO algorithm for infrared image segmentation and defective edge recognition. The FODPSO algorithm helped to overcome the problem of high noise and fuzzy edges of the acquired infrared images. Guo et al. [20] developed a FODPSO algorithm for optic disc localisation and segmentation. The objective function used by the FODPSO algorithm was the between-class variance. The effectiveness of the algorithm was computed by experimenting on the retinal images from DRION, MESSIDOR, ORIGA, and other public databases.

3. Image Segmentation Using Multiobjective Algorithms

In recent years, researchers have explored the use of multiobjective optimization algorithms for image segmentation. Multiobjective optimization involves simultaneously optimizing multiple objectives, which in the context of image segmentation can correspond to different measures of segmentation quality, such as boundary adherence, region homogeneity, and compactness. By optimizing multiple objectives, multiobjective algorithms can produce diverse sets of solutions that can capture different trade-offs between segmentation criteria. Several multiobjective algorithms have been proposed for image segmentation, such as NSGA-II, MOEA/D, and MOGWO.

Zhe Liu [21] proposed an unsupervised image segmentation method using multiobjective PSO (UISMOPC) with two objective functions. This method was tested on the data obtained from the Berkeley segmentation dataset. From the experiments conducted, it was concluded that the UISMOPC algorithm is superior to the traditional K-means, FCM, and other clustering algorithms based on single objective functions. Maryam et al. [22] developed a MOPSO algorithm with two objective functions based on the entropy calculation of the image. This method provided good segmentation results when applied to some standard images. Hinojosa et al. [23] proposed a multiobjective colour thresholding method to reduce the overlapping effect on segmented images. This method was evaluated on the Berkeley image dataset and results showed that the multiobjective colour thresholding method provided better segmentation over traditional single-objective approaches by reducing overlapped areas on the image. A method for segmentation of human brain MRI using a multiobjective optimization approach based on fuzzy entropy clustering and region-based active contour was proposed by Pham et al. [24]. This algorithm was tested on simulated MRI and real MRI from the McConnell Brain Imaging Center (BrainWeb) and Internet Brain Segmentation Repository (IBSR). The proposed technique achieved superior segmentation performance in terms of accuracy and robustness. Elaziz et al. [25] proposed a multiobjective multiverse optimization algorithm for the segmentation of grayscale images. Kapur and Otsu were the two objective functions used. This method was tested on 11 natural grayscale images and was found to provide a better pareto optimal front than other algorithms in terms of hypervolume and spacing. Multiobjective grey wolf optimization (MOGWO), an extension of the grey wolf optimization algorithm was introduced by Oliva et al. [26]. Experiments were conducted using this algorithm on a set of popular natural grayscale images by calculating performance metrics such as PSNR, SSIM, fitness function, and CPU time. The MOGWO based on Kapur and Otsu functions achieved better segmentation results compared to other existing algorithms. Another image segmentation method based on multiobjective artificial bee colony optimization was introduced by Sag and Cunkas [27]. This method was applied to several natural images obtained from the Berkeley segmentation database. The segmentation results obtained from this method were found to be better than FCM.

4. Image Segmentation Using Superpixel Algorithm

Superpixels are a group of pixels that share similar properties, such as colour or texture. Superpixel-based segmentation has become increasingly popular in recent years due to its ability to provide a more compact representation of an image and improve the accuracy of segmentation. In most of the studies, a superpixel algorithm combined with other segmentation algorithms was found to improve segmentation accuracy .

Albayrak Abdulkadir [28] proposed a simple linear iterative clustering (SLIC) superpixel segmentation method and convolutional neural network (CNN) method to segment cells from histopathology images. This method had two stages: firstly, a pre-segmentation was performed using a SLIC superpixel method and then a CNN-based deep learning method was used to classify those superpixels to obtain the final segmentation. The performance of the method was tested on kidney renal cell carcinoma histopathological images of The Cancer Genome Atlas (TCGA) data portal. An overall accuracy of 0.98 was obtained. Albayrak and Bilgin [29] proposed a two-staged superpixel algorithm for the segmentation of cells from histopathology images. In the first stage, the images were segmented using the SLIC method and then the superpixels were clustered using clustering-based segmentation algorithms. The performance of this algorithm was tested on high-resolution histopathological images of renal cell carcinoma, selected from the TCGA data portal. Ding et al. [30] proposed an image segmentation algorithm based on superpixel clustering. In the first step, the images were divided into a set of superpixels using superpixel pre-processing techniques. Next, a spectral clustering algorithm was applied to cluster the superpixel regions and to obtain the final segmented image. This algorithm was tested on the satellite images from the UC Merced Land Use Dataset and the experimental results showed that this algorithm gave a better performance over other traditional spectral clustering algorithms. Zhang et al. [31] proposed a method based on the superpixel and expectation maximization (EM) algorithms for the segmentation of leaves with plant diseases. Firstly, the superpixel algorithm divided the images into several superpixels, and then the EM algorithm was applied to segment the lesion pixels from the image. Experimental results showed that the proposed method was appropriate for plant disease leaf image segmentation.

Table 1 gives a summary of the related works in image segmentation using PSO, multiobjective algorithms, and superpixel algorithm. From the table, it is clear that PSO and its variants are used for image segmentation, but very little work has been carried out on PSO and its variants on histopathology segmentation. It can be noted that MOPSO has never been applied to histopathology image segmentation. The superpixel algorithm is found to improve the segmentation accuracy of other segmentation algorithms.

Table 1. The summary of the related works in image segmentation.

Algorithms	Method	Images
PSO and its variants	PSO-based Otsu's multilevel thresholding [12]	Histopathology images
	PSO-based clustering method [13]	Histopathology images
	PSO-based multilevel thresholding [14]	Grayscale images and medical images
	Dynamic PSO [15]	Real crystal growth images
	PSO using Kapur's and Tsallis entropy [16]	Normal brain MRI
	PSO-FCM algorithm [17]	Ultrasonic teeth images
	DPSO [18]	Satellite images
	FODPSO [19]	Infrared images
	FODPSO [20]	Retinal images

Algorithms	Method	Images
Multiobjective algorithms	UISMOPC [21]	Standard images
	MOPSO [22]	Standard images
	Multiobjective colour thresholding [23]	Standard images
	Multiobjective optimization [24]	Simulated MRI and MRI
	Multiobjective multiverse optimization [25]	Natural grayscale images
	Multiobjective grey wolf optimization [26]	Natural grayscale images
	Multiobjective artificial bee colony [27]	Standard images
Superpixel algorithm	SLIC and CNN [28]	Histopathology images
	SLIC and clustering algorithm [29]	Histopathology images
	Superpixel algorithm and clustering algorithm [30]	Satellite images
	superpixel and EM [31]	Plant disease leaves images

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