Chapter 2
Image Segmentation: A Review

2.1 Introduction

This chapter intends to provide a brief review of different image segmentation techniques. Image segmentation techniques are broadly classified into two categories, viz. classical and non-classical approaches. Most of the classical approaches depend on filtering and statistical techniques. Methods in this direction engage thresholding techniques, edge detection or boundary based techniques, region-based techniques, morphological techniques, normalised cut—a graph theoretic approach, k-means approaches, etc. The non-classical approaches consisting of the fuzzy-neuro-genetic paradigm or its variants are contributed with features for real time applications.

This chapter presents a brief survey of the aforestated trends in image segmentation techniques.

2.2 Classical Approaches to Image Segmentation

Several classical approaches of image segmentation and analysis have been reported in the literature [93, 94]. One of the important techniques for image segmentation is the thresholding technique. This technique deals with the pixel value of an image, such as grey level, colour level, texture, to name a few. In this technique, it is presumed that the adjacent pixel values lying within a certain range belong to the same class [93]. The main objective of this technique is to determine the threshold value of an image. The pixels whose intensity values exceed the threshold value are assigned in one segment and the remaining to the other. The image segmentation approaches using histogram thresholding techniques can be found in the literature [17, 117]. The histogram thresholding technique based on the similarity between grey levels has been demonstrated in [118]. In this article, a mathematical model has been derived using the fuzzy framework. Image segmentation using entropy-based thresholding

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techniques have been demonstrated in [117, 119]. Afrin and Asano [120] proposed a grey level thresholding algorithm on the basis of the relationship between the image thresholding problem and cluster analysis. The cluster similarity measure, applied to determine the threshold value, is the main criteria of this algorithm. The criterion-based concept to select the most suitable greyscale as the threshold value has been employed for many thresholding techniques. The Otsu's [121] thresholding method, one of the oldest methods, has been utilised to analyse the maximum separability of classes. This method has been used to determine the goodness of the threshold value that includes evaluating the heterogeneity between both classes and the homogeneity within every class. In [122], a criterion function has been applied in the threshold selection method based on cluster analysis. The criterion function is generated on the basis of the histogram of the image as well as the information on spatial distribution of pixels. This function has been applied to determine the intra-class similarity to attain the homogeneous and heterogeneous class differentiated by the inter-class similarity. A colour image segmentation method by pixel classification in a hybrid colour space which is adjusted to analyse the image, has been presented by Vandenbroucke et al. in [123]. Tan and Isa [124] proposed a hybrid colour image segmentation technique based on histogram thresholding and fuzzy c-means algorithm. In this technique, the histogram thresholding method has been applied to determine the consistent regions in the colour image. This step is followed by fuzzy c-means algorithm for the betterment of the compactness of the segments. The drawback of the histogram thresholding technique is that this technique overlooks all the spatial relationship information of the images except the pixel intensity. Hence, this technique cannot be efficiently applied for blurred images or for multiple image component segmentation.

Another classical image segmentation technique is the edge detection or boundary based technique. In these techniques, it is assumed that the pixel values change abruptly at the edges between two regions in the image [93]. Few simple edge detector operators such as the Sobel [93] or Roberts [93] operators or more complex ones such as the Canny operator [93] have been applied in these techniques. The derived discontinuous or over-detected edges are obtained by most of the existing edge detectors. However, it is desirable that the output of the actual region boundaries should be closed curves. The closed region boundaries can be prevailed by some post-procedures, such as edge tracking, gap filling, smoothing and thinning. Different edge detection techniques for image segmentation have been reported in different literatures [125, 126]. Sumengen and Manjunath [125] presented a multiscale edge detection technique for segmenting natural images. This approach is quite efficient to annihilate the necessity of explicit scale selection and edge tracking methods. An edge detection and image segmentation technique by designing a vector field has been proposed in [126]. In this method, the location where the vectors diverge from each other in opposite directions has been noted as the edges. A novel automatic image segmentation technique is presented by integrating an improved isotropic edge detector and a fast entropic thresholding technique in [127]. The main geometric structures of an image are evaluated by the derived colour edges. The initial seeds for seeded region growing are determined from the centroids between the adjacent edge regions. The centroids of the generated homogeneous image regions are then used to substitute these seeds by integrating the required additional pixels step by step. The main drawbacks of the edge detection technique are that these do not work well when images have many edges because in that case the segmentation method produces an over segmented result, and it cannot easily identify a closed curve or boundary. However, the global and continuous edges have been detected by the edge-based methods quite efficiently. An automated model-based image segmentation is presented by Brejl and Sonka [19, 128]. In this literature, a training set of two types of models, objects shape model and border appearance model, are maintained for segmentation. The image segmentation is done in two steps. The approximate location of the object of interest is determined in the first step, and in the next step that object is segmented using the shape-variant Hough transform method.

Region-based techniques have been widely used to solve image segmentation problems. The working principle of this technique is that it is assumed that the adjacent pixels in the same region possess similar visual features such as grey level value, colour value or texture. Split and merge [93], a well-known technique for region-based image segmentation, is very much dependent on the selected homogeneity criterion [129]. In region-growing or merging techniques, the input image is first fitted into a set of homogeneous primitive regions. After that, similar neighbouring regions are merged according to a certain decision rule using an iterative merging process [93]. On the other hand in splitting techniques, the entire image is initially regarded as one rectangular region. This process is terminated when all the regions of the image are homogeneous as each heterogeneous image region of the image is divided into four rectangular segments in each step. In split-and-merge techniques, after the splitting stage a merging process is applied for unifying the resulting similar neighbouring regions [93]. Basically, region-based techniques are greedy techniques following the intuitive process to continuously merge/split the regions based on some criteria. A heuristic segmentation approach based on region-merging method has been applied on oversegmented images in [130]. In this method, the characteristics of each pixel of the input image have been used to guide the merging process. Adams and Bischof [131] proposed a hybrid method of seeded region growing (SRG) for image segmentation. In this method, the SRG technique is controlled by a number of initial seeds without tuning the homogeneity parameters. The main objective of this method is that each connected component of a region is assigned with one of the seeds to find an accurate segmentation of images into regions. The regions are constructed by merging a pixel into its nearest neighbouring seed region. An automatic seeded region-growing algorithm for colour image segmentation has been presented in [132]. Gomez et al. [133] proposed an automatic seeded region-growing algorithm, named ASRG-IB1, to segment colour and multispectral images. In this method, the histogram analysis for each band is applied to generate the seeds automatically and an instance-based learning process is used as distance criterion. However, the problem of seeded region-growing technique is the automatic selection of the initial seeds to provide an accurate image segmentation. Lie et al. [134, 135] presented a variant of the level set method to segment an image. In this method, a piecewise constant level set formulation is introduced for identifying the separating regions in different phases. Storage capacity is also benefited by this approach. An unsupervised stochastic model based method to segment an image is presented by Guo and Ma [136, 137]. In this method, parameter estimation and image segmentation is done on the basis of Bayesian learning. A competitive power-value based approach is introduced to segment the images into different classes.

Mathematical morphology [93, 138] dealing with geometrical features, is a well-suited technique for segmentation purposes. Basically from the scientific perspective, the word morphology indicates a particular area of biology that handles the form and structure of animals and plants. In image processing, mathematical morphology has been applied for analysing and representing the geometric structures inherent within an image, such as boundaries, skeletons and convex hulls. Two basic operations of the mathematical morphology are erosion and dilation. These operators create an opening operator in which the erosion operator is applied to an image followed by the dilation operator. Watershed transformation is a powerful morphological tool for image segmentation [93]. Gauch [139] applied watershed transformation on gradient images to obtain an initial segmentation. The scale-based watershed region hierarchies are generated through multiscale analysis of intensity minima in the gradient magnitude. This approach usually yields the oversegmented result of an image. Belaid and Mourou [140] presented an approach to overcome this oversegmentation by the watershed transformation in combination with a topological gradient approach. The multiscale morphological approach [141] has been applied quite efficiently to segment grey level images consisting of bright and dark features of various scales. The potential regions at various scales have been identified at the first step followed by segment validation which has been done using three criteria, such as growing, merging and saturation. An unsupervised morphological clustering method [142] for colour image segmentation has been applied to analyse bivariate histogram. In this method, a segmentation fidelity and segmentation complexity based energy function is presented to measure the multiscale image segmentation quality. The merging of the oversegmented regions is also performed based on that energy function.

Out of the existing image enhancement procedures, the normalised cut—a graph-theoretic approach has become very popular over the years for addressing the problem of image segmentation. Shi and Malik [143] proposed a general image segmentation approach based on normalised cut by solving an eigensystem of equations. In this method, the normalised cut has been applied to partition the image to handle the image segmentation problem. The total likelihood within the regions has been measured by the normalised cut criterion. Images consisting of texture and non-texture regions can be segmented based on local spectral histograms and graph partitioning methods [144–146]. Yang et al. [145] proposed an image segmentation method referred to as the First Watershed Then Normalised Cut (FWTN) method, based on watershed and graph theory. The mean shift analysis (MS) algorithm has been proposed by Comaniciu and Meer [146] to determine the exact estimation of the colour cluster centres in colour space. The MS clustering method [147] can also be employed for designing an unsupervised multiscale colour image segmentation algorithm. In this algorithm, a minimum description length criterion has been applied to merge the resultant oversegmented images. Mean shift (MS) and normalised cut can be applied to segment colour images [148] as well. The discontinuity property of images can be maintained by the mean shift algorithm to form segmented regions. Finally, the normalised cut can be used on the segmented regions to reduce the complexity of the process. This segmentation algorithm provides superior outcome as it is applied on the adjacent regions instead of image pixels. Wang and Siskind [149] developed a cost function, named as ratio cut, based on the graph reduction method to segment colour images efficiently. This cost function works efficiently with region-based segmentation approaches as well as pixel-based segmentation approaches. A graph partitioning approach for segmenting colour images has been demonstrated in [150]. In this method, the colour images are oversegmented using the watershed method and the final segmented images are derived by a graph structure based merging method. A hierarchical structure, named the binary partition tree [151], has been applied for filtering, retrieval, segmentation and image coding purposes. Malik et al. [136, 152] introduced a graph partitioning method to segment an image. In this method, an algorithm is presented for partitioning greyscale images into different regions on the basis of brightness and texture of the image. A graph theoretic framework of normalised cuts is used to divide the image into the regions of coherent texture and brightness. Belongingness of two nearby pixels to the same region is measured by this graph theoretic framework.

The k-means algorithm is one of the simplest and most popular iterative clustering algorithm [87, 153]. The procedure follows a simple and easy way to classify a given dataset to a certain number of clusters. The cluster centroids are initialized randomly or derived from some a priori information. Each data in the dataset is then assigned to the closest cluster. Finally, the centroids are reassigned according to the associated data point. This algorithm optimises the distance criterion either by maximising the intercluster separation or by minimising the intra-cluster separation. The k-means algorithm is a data-dependent greedy algorithm that may converge to a suboptimal solution. An unsupervised clustering algorithm, using the k-means algorithm, is presented by Rosenberger and Chehdi in [154]. An improved k-means algorithm for clustering is presented in [155]. In this method, each data point is stored in a *kd*-tree and it is shown that the algorithm runs faster as the separations between the clusters increase.

Most of the classical approaches discussed above, need some *a priori* knowledge regarding the image data to be processed either in the form of the underlying intensity distribution or about appropriate parameters to be operated upon. The other approaches based on the soft computing methods, however, operate on the underlying data regardless of the distribution and operating parameters.

2.3 Soft Computing Approaches to Image Segmentation

Soft computing techniques, viz. neural network, fuzzy logic and genetic algorithms, have been applied for image segmentation extensively in many literatures. A detailed survey of image segmentation using soft computing techniques is depicted in the following subsections.

2.3.1 Neural Network Based Image Segmentation

Segmentation and clustering of image data followed by the extraction of specified regions can be accomplished by neural networks due to the inherent advantages of adaptation and graceful degradation offered by them [39, 50, 156–160]. Kohonen's self-organising feature map (SOFM) [39] is a competitive neural network used for data clustering. Jiang and Zhou [157] presented an image segmentation method using the SOFM. The pixels of an image are clustered with several SOFM neural networks and the final segmentation is obtained by grouping the clusters thus obtained. The Hopfield's network [57, 161], is a fully connected network architecture with capabilities of auto-association, proposed in 1982. A photonic implementation of the Hopfield network using an optical matrix-vector multiplier is applied to binary object segmentation [162]. An image is segmented by the parallel and unsupervised approach using the competitive Hopfield neural network (CHNN) [128, 163]. In this work, the pixel clustering is done on the basis of the global information of the grey level distribution and a winner-take-all algorithm is employed to emulate the state transitions of the network. Kosko [60, 164] introduced the bi-directional associative memory (BAM) model which evidences similar network dynamics as the Hopfield model. Several image segmentation and pattern recognition processes by self-organising neural network architectures are reported in different literatures [165–167]. Image pixels are one of the criteria in the image segmentation arena for their global feature distribution [168, 169]. Chi [170] presented a new SOM-based k-means method (SOM-K) followed by a saliency map-enhanced SOM-K method (SOMKS) for natural image segmentation. In the preliminary step, the network is trained with intensity value of the pixels and different features of the colour space and after that the k-means clustering algorithm is applied to segment the image. The self-organising neural network (SONN) is introduced to segment textural image in the literature [136, 171]. The SONN architecture for textural image segmentation is based on the orientation of the textures within the images. The binary objects from a noisy binary colour image can be extracted quite efficiently using a single multilayer self-organising neural network (MLSONN) [3] by means of self-supervision. In this network, the standard backpropagation algorithm has been used to adjust the network weights with a view to arriving at a convergent stable solution. A layered version of the same has been proposed in [134, 172, 173] to deal with multilevel objects at the expense of a greater network complexity. However, the multilevel objects cannot be extracted from an image by this network as it uses the bilevel sigmoidal activation function. Bhattacharyya et al. [45, 49, 72, 174] addressed this problem by introducing a functional modification of the MLSONN architecture. They introduced a multilevel sigmoidal (MUSIG) activation function for mapping multilevel input information into multiple scales of grey. The MUSIG activation function is a multilevel version of the standard sigmoidal function which induces multiscaling capability in a single MLSONN architecture. The number of grey scale objects and the representative grey scale intensity levels determine the different transition levels of the MUSIG activation function. The input image can thus be segmented into different levels of grey using the MLSONN architecture guided by the MUSIG activation function. However, the approach assumes that the information contained in the images are homogeneous in nature, which on the contrary, generally exhibit a varied amount of heterogeneity. Neural networks have often been applied for clustering of similar data [136, 175] by means of a selection of underlying prototypes. Thereafter, each prototype is assigned to a pattern based on its distance form the prototype and the distribution of data. In this approach, the number of clusters is determined automatically. Pixel-based segmentation has been implemented in the literature [136, 176]. In this method, each pixel is assigned to a scaled family of differential geometrical invariant features. Input pixels are clustered into different regions using SOFM. SOFM has also been used for the unsupervised classification of MRI images of brain [134, 177, 178]. The MRI images are decomposed into small size by two-dimensional Discrete Wavelet Transform (DWT). The approximation image is applied to train the SOFM and the pixels of the original image are grouped into different regions.

Jiang et al. [179] presented a literature review on computer-aided diagnosis, medical image segmentation, edge detection, etc. by different neural network architectures. In this article, different techniques as well as different examples of neural network architectures are illustrated for medical image segmentation. A new version of the self-organising map (SOM) network, named moving average SOM (MA-SOM), is applied to segment the medical images [180]. SOFM has also been used to segment medical images through identification of regions of interest (ROI) [159, 160]. A pixel-based two-stage approach for segmentation of multispectral MRI images by SOFM is presented by Reddick et al. in [160, 172]. An unsupervised clustering technique for magnetic resonance images (MRI) is presented by Alirezaie et al. [128, 181]. The Self- Organising Feature Map (SOFM) artificial neural network is proposed to map the features in this method.

Neural networks are well known for their parallelism and ability of approximation, adaptation and graceful degradation [37–48]. Researchers applied neural networking techniques using these features for addressing the problem of colour image processing. Several works have been reported where different neural network architectures have been used in this regard [50, 182]. The competitive learning (CL) is applied for online colour clustering on the basis of the least sum of squares criterion [183]. This CL method efficiently converges to a local optimum solution for colour clustering. Wang et al. [184] proposed a two-stage clustering approach using competitive learning (CL) for fast clustering. The local density centres of the clustering data is identified by the CL and after that an iterative Gravitation Neural Network is applied to agglomerate the resulting codewords in a parallel fashion. The Kohonen self-organising feature map (SOFM) [157, 185, 186] also has the ability of retrieving the dominant colour content of images. The SOFM combined with the adaptive resonance theory (ART) has been applied for segmenting colour images in [185]. Self-organising maps (SOM) [157, 187] which are efficient to retrieve the dominant colour content of images have been widely employed to colour image segmentation arena [188]. An ensemble of multiple SOM networks [157] are employed for colour image segmentation in which segmentation is accomplished by the different SOM networks on the basis of the colour and spatial features of the image pixels. Finally, the desired output is derived by combining the clustered outputs. The primitive clustering results are generated by training the SOM on the basis of a training set of five-dimensional vectors (R, G, B, and x, y) in [186]. The isolated pixels are eliminated during the segmentation of the image which is done by merging the scattered blocks. SOFM is also applied to capture the dominant colours of images in [188]. These dominant colours are further merged to control the ultimate number of colour clusters. A neural network based optimal colour image segmentation method, which incorporates colour reduction followed by colour clustering, is proposed by Dong and Xie [189]. A SOFM network is applied for colour reduction to project the image colours which are represented in a modified $L* \, u * v$ space into a reduced set of prototypes. Finally, simulated annealing is used to find out the optimal clusters with a minimum computation cost in the SOFM-derived prototypes. In [190], a fast convergent network named Local Adaptive Receptive Field Self-organising Map (LARFSOM) is employed to segment colour images efficiently. Neural networks are also able to categorise content based images efficiently [191]. In this method, the region segmentation technique is employed to extract the objects from the background and after that the back propagation algorithm is applied in the neural network for feature extraction. SOFM-based neural network is also applied to segment multispectral Magnetic Resonance Images (MRI) images [192]. A hierarchically divisive colour map for colour image quantization with minimal quantization error has been proposed by Sirisathitkul et al. in [193, 194]. They used the Euclidean distances between the adjacent colours with principal axes along the highest variance of colour distribution, to divide a colour cell into two subcells. SOFMs are used to carry out clustering based on colour and spatial features of pixels. The clustered outputs are finally merged to derive the desired segmentation. A parallel version of the MLSONN (PSONN) architecture [195, 196] consisting of three independent and parallel MLSONNs (for component level processing) has been efficiently applied to extract pure colour images from a noisy background. Each network is used to process the colour image data at the R, G, B component levels. The real-world input colour images are provided as inputs through the source layer of the PSONN architecture [195, 196] and the sink layer finally fuses the processed colour component information into processed colour images. This architecture uses the generalised bilevel sigmoidal activation function with fixed and uniform thresholding. Bhattacharyya et al. [195] introduced a self-supervised parallel self-organising neural network (PSONN) architecture guided by the multilevel sigmoidal (MUSIG) activation function for true colour image segmentation. Since the utilised activation functions use fixed and uniform thresholding parameters, they assume homogeneous image information content.

2.3.2 Fuzzy Based Image Segmentation

Real life images exhibit a substantial amount of uncertainty. The varied amount of vagueness manifested in the colour image intensity gamut can be efficiently handled by fuzzy set theory andfuzzy logic. Fuzzy set theory and fuzzy logic [64–68] are very much familiar techniques in the field of image processing and image classification. A good literature survey of the colour image segmentation using fuzzy logic is presented in the literature [197, 198]. The fuzzy c-means (FCM) clustering algorithm [199] is the most popular method based on membership values of different classes. This technique is efficient in clustering multidimensional feature spaces. Each data point belongs to a cluster to a degree specified by a membership grade. The fuzzy c-means algorithm partitions a collection of n pixels $X_i, i = \{1, \ldots, n\}$ into c fuzzy groups, and finds a cluster centre in each group such that a cost function of dissimilarity measure is minimised. However, the FCM algorithm does not fully utilise the spatial information and it only works well on noise-free images. Ahmed et al. [172, 200] proposed a modified version of the objective function for the standard FCM algorithm to allow the labels in the immediate neighbourhood of a pixel to influence its labelling. The modified FCM algorithm improved the results of conventional FCM method on noisy images. A geometrically guided FCM (GG-FCM) algorithm is introduced in [201], based on a semi-supervised FCM technique for multivariate image segmentation. In this method, the local neighbourhood of each pixel is applied to determine a geometrical condition information of each pixel before clustering. Incorporating the spatial constraints to segmentation algorithms [200, 202] and imposing different features or dissimilarity index that is insensitive to intensity variations in the objective function of FCM [203, 204] are two different classifications of the modified FCM. Rezaee et al. [128, 205] introduced an unsupervised image segmentation technique. The segmentation process is the combination of pyramidal image segmentation with the fuzzy c-means clustering algorithm. The root labelling technique is applied to separate each layer of the pyramid into a number of regions. The fuzzy c-means is applied to merge the regions of the layer with the highest image resolution. The minimum number of objects is grouped by the cluster validity function. An algorithm has been proposed in [134, 206] to segment an image based on fuzzy connectedness using dynamic weights (DyW). Fuzzy connectedness is measured on the basis of the linear combination of an object-feature and homogeneity component using fixed weights.

Fuzzy set theory and fuzzy logic can incorporate the colour and spatial uncertainty and guide the segmentation process [207]. Fuzzy rules have been applied for the region dissimilarity function and the total merging process in [208, 209]. Other fuzzy homogeneity based colour image segmentation methods have been presented in the literature [193, 210]. Yang et al. [211] proposed an eigen-based fuzzy C-means (FCM) clustering algorithm to segment colour images. In this method, the eigenspace is formed by dividing the selected colour pixels of the image. colour image segmentation is achieved by combining the eigenspace transform and the FCM method. A fuzzy min-max neural network based colour image segmentation technique (FMMIS) is proposed by Estevez et al. [212] to detect the image artefacts. The minimum bounded rectangle (MBR) for each object, present in an image, is determined in this method and then the method grows boxes around starting seed pixels to delineate different object regions in the image. Fuzzy logic in combination with the seeded region-growing method is applied for colour image segmentation in [213]. The initial seed in this method is selected with the proposed fuzzy edge detection method which has been used to detect the connected edges. A colour image segmentation algorithm named, eigenspace FCM (SEFCM) algorithm, is efficient to segment the images that have the same colour as the pre-selected pixels [214]. In this method, the colour space of the selected colour pixels of the image is segregated into principal and residual eigenspaces.

Fuzzy techniques can be combined with neural network to segment the multidimensional images, viz. colour, satellite, multi-sensory images [215]. In this approach, a statistics of the features of the framework and the parameters has been generated by analysing different segmented images and this statistics is employed in the segmentation of different images taken under difficult illumination conditions. An incremental Weighted Neural Network (WNN), proposed by Muhammed [216], is employed for unsupervised fuzzy image segmentation. The topology of the input data set is preserved by the interconnected nodes in the proposed network. The fuzziness factor is proportional to the connectedness of the net. Finally, the segmentation procedure is carried out by the watershed clustering method and this process is also applied to determine the number of clusters.

2.3.3 Genetic Algorithm Based Image Segmentation

Genetic algorithms (GAs) [74, 217, 218], randomised search and optimization techniques guided by the principles of evolution and natural genetics, work on the collection of probable solutions in parallel rather than on the domain dependent knowledge. GAs are ideal for those problems that do not have any knowledge about the domain theories of the problem or difficult to formulate the problem. Near optimal solutions with an objective or fitness function are provided by the GAs. Due to generality of the GAs, they are applied to solve the image segmentation problem and only require a segmentation quality measurement criterion. Biologically inspired on principles of natural genetic mechanisms, such as population generation, natural selection, crossover and mutation are applied over a number of generations for generating potentially better solutions. An extensive and detailed work of image segmentation using GAs is depicted by Bhanu et al. [219]. Alander [220] presented and compiled a complete survey on GAs used in image processing. Several notable applications of GA based image segmentation approaches can be found in the literature [172, 219, 221, 222]. Yoshimura and Oe [220, 223] proposed an approach for the clustering of textured images in combination with GA and Kohonen's self-organising map. GA has been applied for the clustering of small regions in a feature space and used for developing the automatic texture segmentation method. A combined approach of genetic algorithm with the K-means clustering algorithm has been employed for image segmentation in [224]. In this method, a fitness function is proposed on the basis of texture features similarity [220]. The hierarchical GA has the ability to cluster an image with a predefined number of regions [134, 225]. An image segmentation algorithm is proposed using the fuzzy rule based genetic algorithm in [134, 226]. A

K-means clustering technique is used in this approach to reduce the search space before the application of the GA. Thereafter, GA is engaged to split the regions. Since, GAs have the capability to generate class boundaries in an N-dimensional data space, a set of nonredundant hyperplanes have been generated in the feature space to produce minimum misclassification of images in [227]. In [228], a three-level thresholding method for image segmentation is presented, based on the optimal combination of probability partition, fuzzy partition and entropy theory. A novel approach of fuzzy entropy is applied for the automatic selection of the fuzzy region of membership function [228, 229]. After that, the image has been translated into fuzzy domain with maximum fuzzy entropy and genetic algorithm has been implemented to determine the optimal combination of the fuzzy parameters. In this method, the thresholding is decided by executing the fuzzy partition on a two-dimensional (2-D) histogram based on fuzzy relation and maximum fuzzy entropy principle. An entropy function, named monotonic, is proposed by Zhao et al. [228, 230] and is evaluated by the fuzzy c-partition (FP) and the probability function (PF) to measure the compatibility between the PP and the FP. This function is also applied to determine the memberships of the bright, the dark and the medium approximately. The GAs in combination with the classical fuzzy c-means algorithm (FCM) is applied for colour image segmentation and the objective function of the FCM is modified by considering the spatial information of image data and the intensity inhomogeneities [231]. This image segmentation method does not require the prefiltering step to eliminate the background.

A novel approach of image segmentation by GA is presented in the literature [128, 136, 232]. Mean square error (MSE) is applied as the criteria to segment an image into regions. Shape and location of the regions are also used as the criteria in this method. An image segmentation method by pixon-based adaptive scale is presented in the literature [158, 233]. The pixon-based image model is a combination of a Markov random field (MRF) model under a Bayesian framework. The pixons are generated by the anisotropic diffusion equation. Feitosa et al. [193, 234] proposed a fitness function based on the similarity of resulting segments to target segmentation. The process is applied to minimise the parameter values by modifying the parameters of the region-growing segmentation algorithm. Manual computation is still required though computation is straightforward and intuitive. This method can easily be adapted to modify parameters of other segmentation methods. Image segmentation using fuzzy reasoning in combination with GAs is presented by Zhu and Basir [235]. In this approach, fuzzy reasoning is done in two steps, a denoising phase and a region-merging phase. The segmentation results are optimised by the genetic algorithms. Yu et al. [136, 236] introduced a image segmentation method using GA combined with morphological operations. In this method, morphological operations are used to generate the new generations.

Sun et al. [237] proposed a clustering technique using neural network and GA. In this method, genetic algorithm based maximum likelihood clustering neural networks (GAMLCNN) is applied for segmentation. A combination of genetic algorithm and wavelet transform based multilevel thresholding method is presented by Hammouche et al. [238] for image segmentation. The appropriate number of thresholds as well as the tolerable threshold value is determined by this method. The wavelet transform is applied to reduce the length of the original histogram and the genetic algorithm is employed to decide the number of thresholds and the threshold values on the basis of the lower resolution version of the histogram.

Medical image segmentation can be handled by the genetic algorithm though the medical images have poor image contrast and artefacts that result in missing or diffuse organ/tissue boundaries [239]. In this article, a detailed review of medical image segmentation using genetic algorithms and different techniques is discussed for segmenting the medical images. Zhao and Xie [240] also presented a good literature survey on interactive segmentation techniques for medical images. Lai and Chang [241] proposed a hierarchical evolutionary algorithms (HEA), mainly a variation of conventional GAs, for medical image segmentation. In this process, a hierarchical chromosome structure is applied to find out the exact number of classes and to segment the image into those appropriate classes. Automatic clustering using differential evolution (ACDE) is applied to extract the shape of the tissues on different type of medical images automatically [242, 243]. Ghosh and Mitchell [242, 244] applied genetic algorithm for segmenting the two-dimensional slices of pelvic computed tomography (CT) images automatically. In this approach, the segmenting curve is used as the fitness function in GA. A hybridized genetic algorithm (GA) with seed region-growing procedure is employed to segment the MRI images [242, 245]. A combined approach of neural network and genetic algorithm is presented in [134, 246] to segment an MRI image.

A genetic algorithm based colour image segmentation method is proposed by Farmer and Shugars [247]. GAs have been used in image segmentation for the optimization of relevant parameters in the existing segmentation algorithms [247]. Image segmentation can be easily devised as an optimization problem to reduce the complexity and redundancy of image data. Zingaretti et al. [193, 248] applied GAs to solve the unsupervised colour image segmentation problem. The most important feature of this method is that it performs multi-pass thresholding. In this process, the genetic algorithm adopts different thresholds during each pass to segment a wide variety of non-textured images successfully. Gong and Yang [249] used quadtrees to represent the original and the segmented images. A two- pass system has been defined in this method, where, in the first pass, a Markov Random field based energy function has been minimised and in the second pass, genetic algorithm has been used for final segmentation. In this process, the multi-resolution framework for using the different strategies at different resolution levels and to accelerate the computation has been implemented using the quadtree. This method is similar to the method by Zingaretti et al. [248]. They also defined a new crossover and three mutation methods for operations on the quadtrees. Pignalberi et al. [193, 250] applied genetic algorithms to search a large solution space that requires a manageable amount of computation time. They used a fitness function that combines different measures to compare different parameters and they concentrated on range images, where the distance between the object and a sensor is employed to colour the pixels. This method can be applied for segmenting the 2D images as well as the out surfaces of 3D objects.

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