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Review of Graph, Medical and Color Image base Segmentation Techniques

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Abstract*—This literature review attempts to provide a brief overview of some of the most common segmentation techniques, and a comparison between them.It discusses Graph based methods, Medical image segmentation research papers and Color Image based Segmentation Techniques. With the growing research on image segmentation, it has become important to categorise the research outcomes and provide readers with an overview of the existing segmentation techniques in each category. In this paper, different image segmentation techniques starting from graph based approach to color image segmentation and medical image segmentation, which covers the application of both techniques, are reviewed.Information about open source software packages for image segmentation and standard databases are provided. Finally, summaries and review of research work for image segmentation techniques along with quantitative comparisons for assessing the segmentation results with different parameters are represented in tabular format, which are the extracts of many research papers.*

Index Terms*—Graph based segmentation technique, medical image segmentation, color image segmentation, watershed (WS) method, F-measure, computerized tomography (CT) images*

I. Introduction

Image segmentation is the process of separating or grouping an image into different parts. There are currently many different ways of performing image segmentation, ranging from the simple thresholding method to advanced color image segmentation methods. These parts normally correspond to something that humans can easily separate and view as individual objects. Computers have no means of intelligently recognizing objects, and so many different methods have been developed in order to segment images. The segmentation process in based on various features found in the image. This might be color information, boundaries or segment of an image. The aim of image segmentation is the domain-independent partition of the image into a set of regions, which are visually distinct and uniform with respect to some property, such as grey level, texture or colour. Segmentation can be considered the first step and key issue in object recognition, scene understanding and image understanding.

Its application area varies from industrial quality control to medicine, robot navigation, geophysical exploration, military applications, etc. In all these areas, the quality of the final results depends largely on the quality of the segmentation. In this review paper we will discuss on graph based segmentation techniques, color image segmentation techniques and medical image segmentation, which is the real time application and very important field of research. The mathematical details are avoided for simplicity.

II. SEGMENTATION METHODS

2.1 Graph Based Methods:

A family of graph-theoretical algorithms based on the minimal spanning tree are capable of detecting several kinds of cluster structure in arbitrary point sets [1][2]. In the year 1971,C. T. Zahn presented a paper, where brief discussion is made of the application of cluster detection to taxonomy and the selection of good feature spaces for pattern recognition. Detailed analyses of several planar cluster detection problems are illustrated by text and figures. The well-known Fisher iris data, in four-dimensional space, have been analysed by these methods.During 1993,N.R. Pal and S.K. Pal [3] presented a review paper on image segmentation techniques. They mentioned that, selection of an appropriate segmentation technique largely depends on the type of images and application areas. It has been established by Pal and Pal that the grey level distributions within the object and the background can be more closely approximated by Poisson distributions than that by the normal distributions. An interesting area of investigation is to find methods of objective evaluation of segmentation results. It is very difficult to find a single quantitative index for this purpose because such an index should take into account many factors like homogeneity, contrast, compactness, continuity, psycho-visual perception, etc. Possibly the human being is the best judge for this.N.R. Pal and D. Bhandari [4] presented a paper in 1993. The segmentation of an image is a partitioning of the picture into connected subsets, each of which is uniform, but no union of adjacent subsets is uniform. Kittler and Illingworth suggested an iterative method for minimum error thresholding assuming normal distributions for the gray level variations within the object and background. The computational steps required implementing the method of Kittler and Illingworth have been derived assuming Poisson distribution for the gray level variation within the object/background. The method proposed by pal & pal requires less computation time than the method of Kittler and Illingworth. Attempts have also been made for the objective evaluation of the segmented images using measures of correlation, divergence, entropy and uniformity. Objective evaluation of the thresholds has been done by them using divergence, region uniformity, correlation between original image and the segmented image and second order entropy.In his paper (1996), Y. J. Zhang[5] investigates how the results of object feature measurement are affected by image segmentation. Seven features have been examined by Yu Jin Zhang under different image conditions using a common segmentation procedure. The results indicate that accurate measures of image properties profoundly depend on the quality of image segmentation. As there is currently no general segmentation theory, the empirical methods are more suitable and useful than the analytical methods for performance evaluation of segmentation algorithms [6]. A number of controlled tests are carried out to examine the dependence of feature measurements on the quality of segmented images. In the year 1997, Mark Tabb et al.[7] proposed an algorithm for image segmentation at multiple scales, concerned with the detection of low level structure in images. It describes an algorithm for image segmentation at multiple scales. Jianbo Shi and Jitendra Malik [8] in the year 2000, proposed a novel approach for solving the perceptual grouping problem in vision. Normalized cut is an unbiased measure of disassociation between subgroups of a graph and it has the nice property that minimizing normalized cut leads directly to maximizing the normalized association, which is an unbiased measure for total association within the subgroups. Bir Bhanu and Jing Peng[9]presented a general approach to image segmentation and object recognition that can adapt the image segmentation algorithm parameters to the changing environmental conditions. Rather than focusing on local features and their consistencies in the image data, their approach aims at extracting the global impression of an image. They treat image segmentation as a graph partitioning problem and proposed a novel global criterion, the normalized cut, for segmenting the graph. The normalized cut criterion measures both the total dissimilarity between the different groups as well as the total similarity within the groups.Leo Grady and Eric L. Schwartz [10] introduced in the year 2006 an alternate idea that finds partitions with a small isoperimetric constant, requiring solution to a linear system rather than an eigenvector problem. Suggestions for future work are applications to segmentation in space-variant architectures, supervised or unsupervised learning, three-dimensional segmentation, and the segmentation/clustering of other areas that can be naturally modelled with graphs.In Aug. 2010,Lei Zhang et al. [11] first proposed to employ Conditional Random Field (CRF) to model the spatial relationships among image super pixel regions and their measurements. They then introduced a multilayer Bayesian Network (BN) to model the causal dependencies that naturally exist among different image entities, including image regions, edges, and vertices. The CRF model and the BN model are then systematically and seamlessly combined through the theories of Factor Graph to form a unified probabilistic graphical model that captures the complex relationships among different image entities. Using the unified graphical model, image segmentation can be performed through a principled probabilistic inference.

2.2 COLOR IMAGE SEGMENTATION:

Healey [12] includes the edge information to guide the colour segmentation process, while in [13] the authors combine the texture features extracted from each sub-band of the colour space with the colour features using heuristic merging rules. In [14], the authors discuss a method that employs the colour–texture information for the model-based coding of human images, while Shigenaga [15] adds the spatial frequency texture features sampled by Gabor filters to complement the CIE Lab (CIE is the acronym for the Commission International d'Eclairage) colour image information. In order to capture the colour–texture content, Rosenfeld et al. [16] calculated the absolute difference distributions of pixels in multi-band images, while Hild et al. [17] proposed a bottom-up segmentation framework where the colour and texture feature vectors were separately extracted and then combined for knowledge indexing. In papers [113,115–122,127,128,132,133] extraction of colour image and texture are derived as a sequence of serial processes. The study of chromatic content has been conducted by Paschos and Valavanis [18]. Shafarenko et al. [19] explored segmentation of randomly textured colour images. In this approach the segmentation process is implemented using a watershed transform that is applied to the image data converted to the CIE Luv colour representation. The application of the watershed transform results in over-segmentation and to compensate for this problem the resulting regions are merged according to a colour contrast measure until a termination criterion is met. Hoang et al. [20] proposed a different approach to include the colour and texture information in the segmentation process and they applied the resulting algorithm to the segmentation of synthetic and natural images. Their approach proceeds with the conversion of the RGB image into a Gaussian colour model and this is followed by the extraction of the primary colour–texture features from each colour channel using a set of Gabor filters. They applied Principal Component Analysis (PCA) to reduce the dimension of the feature space from sixty to four. The resulting feature vectors are used as inputs for a K-means algorithm that is employed to provide the initial segmentation that is further refined by a region-merging procedure. Segmentation results are obtained by the method using a set of images from Berkeley database [21]. Wang et al. [22] proposed quaternion Gabor filters to sample the colour–texture properties in the image. In their approach the input image is initially converted to the Intensity Hue Saturation (IHS) colour space and then transformed into a reduced biquaternion representation. The paper presented by Jain and Healey [23] where a multi-scale classification scheme in the colour–texture domain has been investigated. The experiments were conducted using several images from the MIT VisTex database (Vision Texture—Massachusetts Institute of Technology) [24] and the segmentation results were visually compared against those returned by JSEG (J-image Segmentation) proposed by Deng and Manjunath [25].

2.2.1 VARIOUS APPROACHES FOR COLOUR EXTRACTION

Among various strategies, the evaluation of the colour attributes in succession was one of the most popular directions of research. A segmentation algorithm has been proposed by Mirmehdi and Petrou [26]. In this paper the authors introduced a colour–texture segmentation scheme where the feature integration is approached from a perceptual point of view. Here, convolution matrices are calculated using a weighted sum of Gaussian kernels and are applied to each colour plane of the opponent colour space (intensity, red–green and blue–yellow planes, respectively) to obtain the image data that make-up the perceptual tower. A related segmentation approach was proposed by Huang et al. [27]. In this paper the authors applied Scale Space Filters (SSF) to partition the image histogram into regions that are bordered by salient peaks and valleys. A well-known technique of colour–texture feature integration approach was proposed by Deng and Manjunath [25] and this algorithm is widely regarded as a benchmark by the computer vision community. The proposed method is referred to as JSEG and consists of two computational stages, namely colour quantisation and spatial segmentation. The segmentation process is defined as a multi-scale region growing strategy that is applied to the J-images, where the initial seeds required by the region growing procedure correspond to minima of local J values. This multi-scale region growing process often generates an over-segmented result, and to address this problem, a post-processing technique is applied to merge the adjacent regions based on colour similarity and the Euclidian distance in the CIE Luv colour space. In general the overall performance of the JSEG algorithm is very good. Results depend on the optimal selection of three parameters specified by the user: the colour quantisation threshold, the number of scales and the merge threshold. They evaluated the performances of the new JSEG-based algorithm and the original JSEG implementation when applied to 150 images randomly chosen from the Berkeley database [21]. In [28,29] the authors replaced the colour quantisation phase of the JSEG algorithm with an adaptive Mean Shift clustering method, while Zheng et al. [30] followed the same idea and combined the quantisation phase of the JSEG algorithm with fuzzy connectedness. Yu et al. [31] attempted to address the over-segmentation problems associated with the standard JSEG algorithm. The authors validated the proposed algorithm on 200 images from the Berkeley database [21] and they reported that the Local Consistency Error (LCE). Krinidis and Pitas [32] introduced an approach called MIS (Modal Image Segmentation). The MIS algorithm was evaluated on all 300 images contained in the Berkeley database [21] using measures such as the Probabilistic Rand (PR) [33], Boundary Displacement Error (BDE) [35], Variation of Information (VI) [36] and Global Consistency Error (GCE) [34]. The MIS colour segmentation technique was compared against four state of the art image segmentation algorithms namely Mean-Shift [26], Normalised Cuts [37], Nearest Neighbour Graphs [27] and Compression based Texture Merging [25]. The unsupervised segmentation of textured colour images has been recently addressed in the paper by Hedjam and Mignotte [38].They proposed a hierarchical graph-based Markovian Clustering (HMC) algorithm. The authors have conducted a quantitative performance evaluation of the proposed technique applied on the Berkeley Database [21] by calculating performance metrics such as Probabilistic Rand Index (PR) [33], Variation of Information (VI) [36], Global Consistency Error (GCE) [34] and Border Displacement Error (BDE) [35]. A split and merge image segmentation technique was implemented for the retrieval of complex images by Gevers [39]. Ojala and Pietikainen [40,41] proposed a split and merge segmentation algorithm. The split process is evaluated using a metric called Merging Importance (MI). If the colour distribution is homogenous, the weights w1 and w2 control the contribution of the texture and colour during the merge process are adjusted in order to give the colour information more importance. If the colour distribution is heterogeneous it is assumed that the texture is the dominant feature in the image and the algorithm allocates more weight to texture in the calculation of the MI values. The merge process is iteratively applied until the minimum value for MI is higher than a pre-defined threshold. Chen and Chen [42] also implemented split and merge approach for colour–texture segmentation. In this algorithm a colour quantisation based on a cellular decomposition strategy was applied in the HSV (Hue Saturation Value) colour space to extract the dominant colours in the image. Next, the extraction of the colour and local edge pattern histograms are performed. P.Nammalwar et al. [43,44] presents a similar strategy for a split and merge segmentation scheme. Garcia Ugarriza et al. [45] proposed an automatic Gradient SEGmentation algorithm (referred to as GSEG) for the segmentation. J. Chen et al. [46] implemented an algorithm for the segmentation application of natural images to content-based image retrieval (CBIR). In [47]G.Paschos and Valavanis proposed an approach using a region growing procedure. Fondon et al. [48] performed colour analysis in the CIE Lab space using multi-step region growing and Grinias et al. [49] that proposed a segmentation framework using K-Means clustering followed by region growing in the spatial domain. Freixenet et al. [50] proposed to combine the region and boundary information for colour image segmentation. Sail-Allili and Ziou [51] proposed an approach where the colour–image information is sampled by compound Gaussian Mixture Models. Another related technique was developed by Luis-Garcia et al. [52], where the local structure tensors and the image colour components were combined within an energy minimisation framework to accomplish colour–texture segmentation. A graph-based implementation has been proposed by Han et al. [53]. The colour and texture features are modelled by Gaussian Mixture Models (GMMs) and integrated into a framework based on the Grab Cut algorithm. Kim and Hong [54] also defined the colour image segmentation as the problem of finding the minimum cut in a weighted graph. The experiments were conducted using images selected from the VisTex [24] and Berkeley databases [21]. Level sets approaches have also been evaluated in the context of colour image analysis in the review presented by Crème's et al. [55]. Active contours in capturing complex geometries and dealing with difficult initialisations can be found in [56,57]. Brox et al. [58] propose to combine colour, texture and motion in a level-set image segmentation framework. Zoller et al. [59] formulated the image segmentation as a data clustering process. A related image segmentation approach was proposed by Ooi and Lim [60]. The clustering methods [61] have been widely applied in the development of colour image segmentation algorithms due to their simplicity and low computational cost. Colour–texture segmentation framework (referred to as CTex) [62,63], where colour and texture are investigated on separate channels. The colour image segmentation involves filtering the input data using a Gradient-Boosted Forward and Backward (GB-FAB) anisotropic diffusion algorithm [64] that is applied to eliminate the influence of the image noise and improve the local colour coherence. Campbell and Thomas [65] proposed an algorithm where the extracted colour and texture features are concatenated into a feature vector and then clustered using a randomly initialised Self Organising Map (SOM) network. The proposed segmentation technique was tested on natural images taken from the Bristol Image Database [66] and the segmentation results were compared against manually annotated ground-truth data. Other related approaches that integrate colour and texture features using clustering methods can be found in [67–73]. Liapis and Tziritas [74] proposed an algorithm for image retrieval where the colour and texture are independently extracted. Liapis and Tziritas' first tests were conducted on Brodatz images [75], a database composed of 112 grayscale textures. In addition, the authors also obtained results using 55 colour natural images from VisTex [24] and 210 colour images from Corel Photo Gallery. Martin et al. [76] adopted a different approach for the boundary identification of objects present in natural images. The authors proposed a supervised learning procedure to combine colour, texture and brightness features by training a classifier using the manually generated ground-truth data taken from the Berkeley segmentation dataset [21]. The Normalised Cuts segmentation algorithm [77] and the numerical evaluation was carried out by computing the mean GCE [34], precision, recall and F-measure values for all images in the Berkeley database [21]. Carson et al. [78] proposed a colour–texture segmentation scheme (that is referred to as Blobworld) that was designed to achieve the partition of the input image in perceptual coherent regions. The colour features are extracted on an independent channel from the CIE Lab converted image that has been filtered with a Gaussian operator. For automatic colour–texture image segmentation, the authors proposed to jointly model the distribution of the colour, texture and position features using Gaussian Mixture Models (GMMs). The main advantage of the Blobworld algorithm consists in its ability to segment the image into compact regions. In this approach proposed by Manduchi [79], he has extracted the colour and texture features on independent channels, where the mixture models for each class was estimated using an Expectation-Maximisation (EM) algorithm. Jolly and Gupta [80] followed an approach where the colour and texture features were extracted on separate channels. An approach was adopted by Khan et al. [81]. In their implementation, the input image is converted to the CIE Lab colour space prior to the calculation of the colour and texture features. A related approach was adopted by Fukuda et al. [82] with the purpose of segmenting an object of interest from the background information. The RGB colour features are combined into a multi-dimensional feature vector with the local texture features given by the wavelet coefficients. The colour–texture integration is modelled using Gaussian Mixture Models (GMMs) and the segmentation process is carried out in a coarse-to-fine fashion using an iterative process to find a minimum cost in a graph. Approaches based on Markov Random Field (MRF) models were often employed for texture analysis [83–85]. Other approaches that employed MRF models for colour–texture segmentation include the works detailed in [86–92]. The Local Consistency Error (LCE) and the Global Consistency Error (GCE) [34] are examples of area-based metrics that sample the level of similarity between the segmented and ground-truth data by summing the local inconsistencies for each pixel in the image. The paper [93] describes a multiresolution image segmentation algorithm based on adaptive gradient thresholding, and progressive region growing. The proposed algorithm was tested on the Berkeley segmentation database of 300 images.The Multiresolution Adaptive and Progressive Gradient-based colour image SEGmentation (MAPGSEG) results were qualitatively evaluated utilizing the Berkeley segmentation database consisting of 300 images (of dimensions 321X481), by computing the Normalized Probabilistic Rand index (NPR)[93]. Table 1 represents quantitative evaluation of research work for segmentation techniques.

2.3 Video Segmentation:

Luciano et al.[94] performed an experiment on real and synthetic sequences in April 2010. In this paper they experimented with real and synthetic sequences suggest that our method also could be used in other image processing and computer vision tasks, besides video coding, such as video information retrieval and video understanding. Their work described an approach for object-oriented video segmentation based on motion coherence.

2.4 MEDICAL IMAGE BASED RESEARCH:

In the year 1990, Lawrence M. Lifshitz et al.[95] presented a paper on amultiresolution hierarchical approach to Image Segmentation Based on Intensity Extrema for abdominal CT images. Lawrence & Stephen presented that Stack-based image segmentation correctly isolates anatomical structures in abdominal CT images. The aim of their research has been to create a computer algorithm to segment gray scale images into regions ofinterest (objects). These regions can provide the basis for scene analysis (including shape parameter calculation) or surface-based shaded graphics display. The algorithm creates a tree structure for image description by defining a linking relationship between pixels in successively blurred versions of the initial image. In the year 2000,Dzung, Chenyang & Jerry [93] presented critical appraisal of the current status of semi-automated and automated methods for the segmentation of anatomical medical images and the methods in medical image segmentation. Tonsillitis disease is the cause of cardiac valvular disease and pneumonia. Bacteria causing tonsillitis are responsible for future Mitral valve stenosis and pneumonia. These sequels can be prevented by early diagnosis of disease and finding out the causative pathogens. To improve data transfer rates, Pranithan Phensadsaeng et al.[96] proposed VLSI architecture by using color model for early-state tonsillitis detection. Anusha Achuthan et al.[97]presented a new segmentation method that integrates a wavelet based feature, which is able to enhance the dissimilarity between regions with low variations in intensity. This feature is integrated to formulate a new level set based active contour model that addresses the segmentation of regions with highly similar intensities in medical images, which do not have clear boundaries between them. A major difficulty that is specific to the segmentation of MR images is the 'intensity inhomogeneity artefact, which causes a shading effect to appear over the image.They divided segmentation methods into eight categories: (*a*) thresholding approaches, (*b*) region growing approaches, (*c*) classifiers, (*d*) clustering approaches, (*e*) Markov random field (MRF) models, (f) artificial neural networks, (*g*) deformable models, and (*h*) atlas-guided approaches. Soumik Ukil et al. [98] developed in Feb. 2009, an automatic method for the segmentation and analysis of the fissures, based on the information provided by the segmentation and analysis of the airway and vascular trees. This information is used to provide a close initial approximation to the fissures, using a watershed transform on a distance map of the vasculature. In a further refinement step, this estimate is used to construct a region of interest (ROI) encompassing the fissures. The human lungs are divided into five distinct anatomical compartments called the *lobes*, which are separated by the pulmonary fissures. The accurate identification of the fissures is of increasing importance in the early detection of pathologies, and in the regional functional analysis of the lungs. Soumik Ukil and Joseph M. Reinhardt developed a method to detect incomplete fissures, using a fast-marching based segmentation of a projection of the optimal surface. A new interactive image processing method is proposed by Zhanli Hu et al. [99] Using that method, image smoothing, sharpening, histogram processing, pseudo-colour processing, segmentation, reading, local amplification and measurement for medical image in DICOM format can be realized. The ROI is enhanced using a ridgeness measure, which is followed by a 3-D graph search to find the optimal surface within the ROI. The paper (in the year 2010) presented by Yao-Tien Chen [100] proposes an alternative criterion derived from the Bayesian risk classification error for image segmentation and also proposed model on a level set method based on the Bayesian risk for medical image segmentation. Atfirst, the image segmentation is formulated as a classification of pixels. Then the Bayesian risk is formed by the losses of pixel classification. The proposed model introduces a region-based force determined through the difference of the posterior image densities for the different classes, a term based on the prior probability derived from Kullback–Leibler information number, and is gularity term a dopted to avoid the generation of excessively irregular and small segmented regions.Arnau Oliver et al. [101] presented a paper in 2010. They presented and reviewed different approaches to the automatic and semi-automatic detection and segmentation of masses in mammographic images. Specific emphasis has been placed on the different strategies. Region-based segmentation relies on the principle of homogeneity, which means that there has to be at least one feature that remains uniform for all pixels within a region. Region-based methods can be split in two basic strategies: the well-known region growing and split and merge approaches. A classification of both detection and segmentation techniques has been proposed, describing several algorithms and pointing out their specific features. Dae Sik Jeong et al.[102] presented a paper in the year 2010. They proposed a new iris segmentation method for non-ideal iris images. This paper proposes a new iris segmentation method that can be used to accurately extract iris regions from non-ideal quality iris images. Chuan-Yu Chang et al. [103] proposed a method in June 2010 that includes image enhancement processing to remove speckle noise, which greatly affects the segmentation results of the thyroid gland region obtained from US images. They proposed a complete solution to estimate the volume of the thyroid gland directly from US images. The radial basis function neural network is used to classify blocks of the thyroid gland. The integral region is acquired by applying a specific-region-growing method to potential points of interest. Mustafa et al. [104] presented a new active contour-based, statistical method for simultaneous volumetric segmentation of multiple subcortical structures in the brain. Early papers include the work of Funakubo [105] where a region-based colour–texture segmentation method was introduced for the purpose of biomedical tissue segmentation and Harms et al. [106] where the colour information has been employed in the computation of texton values for blood cell analysis. Celenk and Smith [107] proposed an algorithm that integrates the spatial and spectral information for the segmentation of colour images detailing natural scenes, while Garbay discussed in [108] a number of methods that were developed for the segmentation of colour bone marrow cell images. Katz et al. [109] introduced an algorithm for the automatic retina diagnosis where combinations of features including colour and edge patterns were employed to identify the vascular structures in the input image. Table 2 represents quantitative evaluation for medical image based research work.

III. OPEN SOURCE SOFTWARE PACKAGES FOR IMAGE SEGMENTATION

Several open source software packages are available for performing image segmentation [110]. Open source software packages for performing image segmentation are listed below:

1. ITK - Insight Segmentation and Registration Toolkit (Open Source).
2. ITK-SNAP is a GUI tool that combines manual and semi-automatic segmentation with level sets.
3. GIMP which includes among other tools SIOX (Simple Interactive Object Extraction).
4. VXL is a computer vision library.
5. ImageMagick segments using the Fuzzy C-Means algorithm.
6. 3DSlicer includes automatic image segmentation.
7. MITK has a program module for manual segmentation of gray-scale images.
8. OpenCV is a computer vision library originally developed by Intel.
9. GRASS GIS has the program module i.smap for image segmentation.
10. Fiji - Fiji is just ImageJ, an image processing package which includes different segmentation plug-ins.
11. AForge.NET - an open source C# framework.

There is also software packages available free of charge for academic purposes:

1. GemIdent
2. CVIPtools
3. MegaWave

Open source software for medical image analysis[110]:

Several open source software packages are available for performing analysis of medical images. Open source software packages for performing analysis of medical images are listed below:

1. ImageJ
2. 3D Slicer
3. ITK
4. OsiriX
5. GemIdent
6. MicroDicom
7. FreeSurfer
8. ClearCanvas
9. Seg3D
10. NumPy + SciPy + MayaVi/Visvis
11. InVesalius

3.1 DATABASES& THEIR WEBSITES

Several databases have been proposed by the computer vision community that consist of a large variety of colour images that can be employed in the quantification of colour image segmentation algorithms. Standard database is required for implementation of image segmentation techniques or method on input images. These databases are also useful for evaluation of methods or evaluation of results. It can also be useful for validating the available results by comparisons with the standard database. There are some publicly available databases containing images with colour image segmentation characteristics. They are listed below with their respective websites along with the referred research paper.

Name of Databases	**Database Web address**
Berkeley Segmentation Dataset and Benchmark (2001)	[21] http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/
McGill calibrated colour image database (2004)	[111] http://tabby.vision.mcgill.ca
Outex database (2002)	[112] http://www.outex.oulu.fi/
VisTex database (1995)	[24] http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html
Caltech-256 (2007)	[113]http://www.vision.caltech.edu/Image_Datasets/Caltech256/
The Prague Texture Segmentation Data Generator and Benchmark (2008)	[114] http://mosaic.utia.cas.cz/
Pascal VOC (updated 2009)	[115]http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2009/#devkit
CUReT (1999)	[116]http://www.cs.columbia.edu/CAVE/software/curet/
SIMPLIcity (2001)	[117]http://wang.ist.psu.edu/docs/related/
Minerva (2001)	[118]http://www.paaonline.net/benchmarks/minerva/
The Texture Library Database (updated 2009)	http://textures.forrest.cz
BarkTex (1998)	[119]ftp://ftphost.uni-koblenz.de/outgoing/vision/Lakmann/BarkTex
Corel Commercially available	

TABLE 1: QUANTITATIVE EVALUATION OF RESEARCH WORK FOR SEGMENTATION TECHNIQUES

SR. NO.	SEGMENTATION ALGORITHM/PAPER TITLE	Techniques/Algorithms /Methods	Quantitative Results
1.	Segmentation of colour texturesMirhmedi and Petrou[26]	Edge flow (% misclassified pixels (avg. error))	Error per(%) of incorrectly pixels Test Image MM97 Proposed Method T1 2.8% 0.002% T2 2.6% 0.06% T27 11.4% 1.6%
2.	Colour texture segmentation based on the modal energy of deformable surfacesMIS (Krinidis and Pitas [32])	Proposed technique MIS compared with MS,NC	PR BDE VI GCE Ground truth 0.8754 4.9940 1.1040 0.0797 MIS $_{\gamma=0}$ 0.7869 8.0930 2.0117 0.2110 MIS $_{\gamma=50}$ 0.7981 7.8263 1.9348 0.1942 MIS $_{\gamma=100}$ 0.7912 7.9213 1.9801 0.2022 MS 0.7550 9.7001 2.4770 0.2598 NC 0.7229 9.6038 2.9329 0.2182 NNG 0.7841 9.9497 2.6647 0.1895
3.	Automatic image segmentation by dynamic region growth and multiresolution merging(GSEG).[45]	Proposed technique GSEG compared with JSEG,GRF	GRF JSEG GSEG Avg.Time(sec) 240 16 24 Avg.NPR 0.357 0.439 0.495 Std.Dev.NPR 0.345 0.318 0.306 Environment C C MATLAB
4.	Colour–texture segmentation using unsupervised graph cuts.UGC .[54]	Proposed technique UGC compared with JSEG (Precision-recal, F-measure (avg)	Human JSEG <u>UGC</u> Color Color-texton Precision 0.77 0.42 0.57 0.64 Recall 0.75 0.46 0.49 0.51 F-measure 0.76 0.44 0.53 0.57
5.	CTex—an adaptive unsupervised segmentation algorithm based on colour–texture coherence.[62]	Proposed technique CTex compared with JSEG	PR Index$_{mean}$ PR Index$_{standard_deviation}$ JSEG 0.77 0.12 CTex 0.80 0.10
6.	Segmentation of natural images using self-organising feature maps. [65]	Area overlap	<u>Features Dimensionality Avg. Seg. Accuracy</u> Texture Only 16 36.4% Colour Only 3 55.7% Colour+Texture 19 62.2%
7.	B-JSEG(Wang et al.[120]	Proposed technique B-JSEG compared with JSEG	JSEG HSEG B-JSEG Average error 33.1 29.3 **24.1** Percentage (%)
8.	Unsupervised segmentation of natural images via lossy data compression.CTM [123]	Proposed technique CTM compared with MS,NC,FH	PRI VoI GCE BDE Humans 0.8754 1.1040 0.0797 4.994 CTM$_{\gamma=0.1}$ 0.7561 2.4640 0.1767 9.4211 CTM$_{\gamma=0.15}$ 0.7627 2.2035 0.1846 9.4902 CTM$_{\gamma=0.2}$ 0.7617 2.0236 0.1877 9.8962 MS 0.7550 2.477 0.2598 9.7001 NC 0.7229 2.9329 0.2182 9.6038

			FH 0.7841 2.6647 0.1895 9.9497
9.	Unsupervised multiscale colour image segmentation based on MDL principle. [126]	F-measure	h_s \ h_r: 4.0 4.5 5.0 5.5 6.0 3.0 0.6587 0.6644 0.6720 0.6713 0.6755 3.5 0.6585 0.6631 0.6698 0.6753 0.6802 4.0 0.6625 0.6684 0.6700 0.6714 0.6801 4.5 0.6624 0.6684 0.6699 0.6734 0.6756 5.0 0.6587 0.6680 0.6706 0.6696 0.6742
10.	Colour Image Segmentation Using Soft Computing Techniques[127]	Comparison of HCM, FCM,PFCM and CNN Techniques	PSNR / Compression Ratio / Execution time HCM 28.24 11.15 253.14 FCM 30.57 16.03 1617.1 PFCM 29.53 12.00 2.281 CNN 39.39 17.95 2.125
11.	Morphological Description of Color Images for Content-Based Image Retrieval[129]	Comparison of AC,CSD,CDE,CSG,MHW,MHL to the standard color histogram	Histogram AC CSD CDE CSG MHW MHL 1 127 89 9 548 470 443
12.	Morphological segmentation on learned boundaries.(WF and WS) [132]	Proposed Techniques WF and WS compared with NC	Method GCE Precision Recall F-mea. WF level 2 0.19 0.64 0.37 0.44 NC (6 reg.) 0.29 0.52 0.38 0.42 WS Vol (18 reg.)0.22 0.54 0.60 0.55 NC (18 reg.) 0.23 0.44 0.58 0.48
13.	Textured image segmentation based on modulation models[137]	Proposed Algorithm compared with (DCA)+K means, DCA+WCE	Algorithms / Avg.Values of BCE / Med.Values of BCE Proposed 0.4876 0.5124 DCA+K-Means 0.5454 0.5478 DCA+WCE 0.5044 0.5143
14.	An adaptive and progressive approach for efficient gradient-based multiresolution color image segmentation [141]	Proposed technique MAPGSEG compared with GRF,JSEG and EG	GRF JSEG EG GSEG MAPGSEG Avg.Time(sec) 240 16.2 7.0 24.1 11.1 Avg.NPR 0.357 0.439 0.497 0.495 0.495 NPR>0.7 (# Images) 38 65 68 91 85 Environment C C C MATLAB
15.	Image Segmentation with a Unified Graphical Model [143]	BN and CRF Segmentation model consistency	Algorithm / Overall accuracy TextonBoost 72.2% Yang et al. 75.1% Auto-Context 74.5% Our approach 75.4%

TABLE 2: QUANTITATIVE EVALUATION FOR MEDICAL IMAGE BASED RESEARCH WORK

SR. NO.	SEGMENTATION ALGORITHM/PAPER TITLE	Techniques/Algorithms/Methods	Quantitative Results
1.	Anatomy-Guided Lung Lobe Segmentation in X-Ray CT Images[98]	An automatic method for the segmentation of the lobar fissures on chest CT scans. The method uses the interactive watershed transform, calculated on a vessel distance map, to obtain an initial segmentation	Subject Resolution Graph size Time RMS error factor X Y Z (s) (mm) 1 1.0 215 93 406 40.06 1.55 2 1.0 222 94 400 27.08 1.88 3 1.0 228 104 442 34.55 1.37 4 1.0 230 123 391 47.47 1.49 5 1.0 229 98 417 32.51 1.70
2.	A new iris segmentation method that can be used to accurately extract iris regions from non-ideal quality iris images[102]	Proposed technique a new iris segmentation method	E1 error rate E2 error rate FPR FNR 2.8 14.4 1.2 27.6
3.	Thyroid Segmentation and Volume Estimation in Ultrasound Images[103]	Proposed method copared with AWMF+ACM and AWMF+Watershed model	Segmentation <u>Measurement Indices[%]</u> Methods Accuracy Sensitivity Specificity PPV NPV The proposed 96.54 91.98 97.69 91.17 97.91 Method AWMF+ACM 94.56 85.66 96.90 88.42 92.27 AWMF+ Watershed 88.27 78.80 90.78 70.19 94.14
4.	Coupled Non-Parametric Shape and Moment-Based Inter-Shape Pose Priors for Multiple Basal Ganglia Structure Segmentation[104]	Quantitative accuracy results for the 3D experiments	TPR FPR 1-DC C&V 0.7301 0.0075 0.2680 Coupled Shape 0.7299 0.0050 0.2351 Coupled Shape and 0.7291 0.0049 0.2335 Relative pose
5.	Image structure representation and processing: a discussion of some segmentation methods in cytology[108]	Compared segmentation performances as evaluated according to Human observer diagnosis	Observer type of diagnosis Correct seg. Uncorrect seg. process Relaxation 70 30 Region Growing 93 7 Frontier detection 89 11

IV. CONCLUSION

Color has been widely used for image and video. Since the introduction of color distributions as descriptors of image content, various research projects have addressed the problems of color spaces, illumination invariance, color quantization, and color similarity functions. Many different methods have been developed to enhance the limited descriptive capacity of color distributions. We have presented here the state of the art of color-based methods that can be used to segment color images. The most surprising element that emerges from our study of color indexing and segmentation is that most of the methods analysed do not explore the problem of how to deal with color in a device independent way. Very seldom are details given, or references made to image acquisition and management in terms of standard color coordinates, although it is reasonable to assume that the image database contains images acquired from many sources, and subjected to a number of processing steps before indexing and display. Quantization and segmentation reduce acquisition noise, and may to some extent cope with changes in imaging conditions, but a more rigorous approach to color imaging is surely desirable. Several of the algorithms proposed have been designed to implement machine color constancy, but their application in real world conditions is still under investigation. The very definition of machine color constancy is still a matter for future research, rather than an effective tool that can be employed in current content-based image segmentation engines. Most color based algorithms make it possible to perform searches for the presence of specific colours, but not, with very few exceptions, for their absence. Consequently, it would be desirable to modify segmentation methods so that users can specify which colours should be excluded from the image segmentation. The definition of feature similarity also plays fundamental role image segmentation, as images with "similar" feature distributions are often considered similar in appearance without requiring any semantic expression of this.

The major objective of this paper was to analyse the main directions of research in the field of colour image segmentation and to categorise the main approaches with respect to the colour image segmentation process. After evaluating a large number of papers, we identified three major trends in the development of colour image segmentation, namely algorithms based on feature integration, approaches that integrate the colour and texture attributes in succession and finally methods that extract the colour image features on independent channels and com- bine them using various integration schemes. As we discussed, the methods that fall in the latter categories proved to be more promising when viewed from algorithmic and practical perspectives. However, since the level of algorithmic sophistication and the application domain of the newly proposed algorithms are constantly increasing it is very difficult to predict which approach will dominate the field of colour image analysis in the medium to long term but we believe that the next generation of algorithms will attempt to bridge the gaps between approaches based on sequential feature integration and those that extract the colour image features on independent channels. Currently, the main research area in the field of colour image segmentation is focused on methods that integrate the features using statistic/probabilistic schemes and methods based on energy minimisation. However in line with the development of new algorithms an important emphasis should be placed on methodologies that are applied to evaluate the performance of the image segmentation algorithms. We feel that this issue had not received the attention that it should deserve and as a result the lack of widely accepted metrics by the computer vision community made the task of evaluating the appropriateness of the developed algorithms extremely difficult. Although substantial work needs to be done in the area of performance evaluation, it is useful to mention that most of the algorithms that have been recently published had been evaluated on standard databases and using well-established metrics. Also, it is fair to mention that the publicly available datasets are not sufficiently generic to allow a comprehensive evaluation, but with the emergence of benchmark suites such as Berkeley database this issue starts to finally find an answer. We believe that this review has thoroughly sampled the field of colour image segmentation using a systematic evaluation of a large number of representative approaches with respect to feature integration and has also presented a useful overview about past and contemporary directions of research. To further broaden the scope of this review, we have also provided a detailed discussion about the evaluation metrics, we examined the most important data collections that are currently available to test the image segmentation algorithms and we analysed the performance attained by the state of the art implementations. Finally, we cannot conclude this paper without mentioning the tremendous development of this field of research during the past decade and due to the vast spectrum of applications, we predict that colour image segmentation analysis will remain one of the fundamental research topics in the foreseeable future.

Most of the methods described here have been tested on different databases, of very different sizes, ranging from two to more than thousand images, for different segmentation tasks. This makes it extremely difficult, if not impossible, to provide an absolute ranking of the effectiveness of the algorithms. We can make the general observation that color alone cannot suffice to index large, heterogeneous image databases. The combination of colour with other visual features is a necessary approach that merits further study. Much more dubious, instead, are methods that assume that affordable, unsupervised image segmentation is always possible, and that the evaluation of image similarity can be dealt with as a graph matching problem, with a reasonable computational burden. The design of a segmentation system must address issues of efficiency in addition of those of effectiveness. A promising direction for future research is, in our opinion, the exploitation of colour image similarity for image database navigation and visualization is an attempt in this direction and the segmentation of colour images based on psychological effects. We would like to see new generation systems that support querying by emotions and open-ended searches in the image database where similar images are located next to each other. We would also like to see new generation systems by combination of various segmentation techniques (hybrid techniques) along with solving content based query on real time colour images as well as solving online applications. There is no universal theory on colour image segmentation still now. All of the existing colour image segmentation approaches are by nature ad hoc. They are strongly application dependent, in other words, there are no general algorithms and colour space that are good for all colour images. An image segmentation problem is basically one of psychophysical perception, and it is essential to supplement any mathematical solutions by a priori knowledge about the picture knowledge. Most gray level image segmentation techniques could be extended to color image, such as histogram thresholding, clustering, region growing, edge detection and fuzzy based approaches. They can be directly applied to each component of a colour space, and then the results can be combined in some way to obtain the final segmentation result. However, one of the problems is how to employ the colour information as a whole for each pixel. When colour is projected onto three components the colour information is so scattered that the colour image becomes simply a multispectral image and the colour information that human can perceive is lost. Another problem is how to choose the colour representation for segmentation, since each colour representation has its advantages and disadvantages. In most of the existing colour image segmentation approaches, the definition of a region is based on similar colour. This assumption often makes it difficult for many algorithms to separate the objects with highlights, shadows, shading or texture which cause inhomogeneous colours of the objects surface. Using HSI can solve this problem to some extent except that hue is unstable at low saturation. Some physics based models have been proposed to find the objects boundaries based on the type of materials, but these models have too many restrictions which limit them to be extensively employed. The fuzzy set theory has attracted more and more attention in the area of image processing. Fuzzy set theory provides us with a suitable tool which can represent the uncertainties arising in image segmentation and can model the cognitive activity of the human beings. Fuzzy operators, properties, mathematics and inference rules IF_THEN rules, have found more and more applications in image segmentation. Despite the computational cost, fuzzy approaches perform as well as or better than their crisp counterparts. The more important advantage of a fuzzy methodology lies in that the fuzzy membership function provides a natural means to model the uncertainty in an image. Subsequently, fuzzy segmentation results can be utilized in feature extraction and object recognition phases of image processing and computer vision. Fuzzy approach provides a promising means for colour image segmentation.

In summary, we covered state of art color image segmentation techniques,comparisons of segmentation techniques, brief about assessment parameters, review of research work in tabular way for quick reference. We have also mentioned many open source software for implementation work for image segmentation, as well as also mentioned standard databases for algorithms' validation purposes, in keeping mind for larger interest of research community.

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