A REVIEW ON IMAGE SEGMENTATION TECHNIQUES WITH REMOTE SENSING PERSPECTIVE

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ABSTRACT:

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 applied on optical remote sensing images are reviewed. The selection of papers include sources from image processing journals, conferences, books, dissertations and thesis out of more than 3000 journals, books and online research databases available at UNB. The conceptual details of the techniques are explained and mathematical details are avoided for simplicity. Both broad and detailed categorisations of reviewed segmentation techniques are provided. The state of art research on each category is provided with emphasis on developed technologies and image properties used by them. The categories defined are not always mutually independent. Hence, their interrelationships are also stated. Finally, conclusions are drawn summarizing commonly used techniques and their complexities in application

1. INTRODUCTION

Image segmentation in general is defined as a process of partitioning an image into homogenous groups such that each region is homogenous but the union of no two adjacent regions is homogenous (Pal and Pal, 1993). Efficient image segmentation is one of the most critical tasks in automatic image processing (Pavlidis, 1988; Haralick and Shapiro, 1985; Pal and Pal, 1993; Zhang, 1997; Cheng et al., 2001). Image segmentation has been interpreted differently for different applications. For example, in machine vision applications, it is viewed as a bridge between low level and high level vision subsystems (SpirKovska, 1993), in medical imaging as a tool to delineate anatomical structure and other regions of interest whose a priori knowledge is generally available (Pham et al., 2000) and in statistical analysis, it is posed as a stochastic estimation problem, with assumed prior distributions on image structure, which is widely used in remote sensing (Kerfoot et al., 1999). In remote sensing, it is often viewed as an aid to landscape change detection and land use/cover classification. Aforementioned examples state that image segmentation is present in every kind of image analysis. This constitutes a plethora of literature on the image segmentation. This necessitates the organized categorisation of them. In order to present an organized review on image segmentation techniques, this review paper limits its analysis to optical remote sensing image analysis. This is essential because radar image segmentation is another horizon in remote sensing image analysis. From now onwards, remote sensing image would refer only to optical satellite remote sensing images.

Optical remote sensing imagery has been to a paradigm shift in the decade after year 1999. Landsat 7 launched in 1999 (with Multispectral (MS), 30m spatial resolution; Panchromatic (Pan), 15m spatial resolution), IKONOS launched in 1999 (MS, 4.0m; Pan, 1.0m), Quickbird launched in 2001 (MS, 2.44m; Pan, 0.61m), WorldView-1 launched in 2007 (Pan, 0.5m), GeoEye-1 launched in 2008 (MS, 1.65m; Pan, 0.42m), and WorldView-2 launched in 2009 (MS, 1.8m; Pan, 0.46m) are evidence of this shift. The spatial resolution has been changed so considerably that pixel size has become smaller than a size of car which was earlier bigger than two or three buildings. This led to research on new classification algorithms for high and very high resolution remote sensing images because traditional pixel based analysis was proved to be insufficient due to its incapability to handle the internal variability of complex scenes (Schiewe, 2002; Blaschke and Strobl, 2001; Carleer et al., 2005). These also propelled object based approach or Object Based Image Analysis (OBIA) for very high resolution image segmentation (Hay and Castilla, 2006). Detailed applications and discussion on the development trends of OBIA can be found in Blaschke (2010). However, in this paper applications based on OBIA are not the concern. This paper deals with technological aspect of image segmentation, which concern about identification of objects but not much related to further analysis of the object. Still object analysis is required for assessment of segmentation accuracy.

According to the aforementioned definition of segmentation, the major thrust is on determining the suitable homogeneity measure which can discriminate the objects from each other. Some examples of the measures may be spectral, shape, texture and contexture. Most of the methods applied on remote sensing imageries are imported from other fields (Color image segmentation, Medical Image segmentation etc) and they work well because the underlying principal is same. For example, Cheng et al. (2001) extended the application of monochrome (single band) segmentation method, which was originally used on medical imagery, to colour image segmentation (three bands).

With the numerous recent developments of new segmentation methodologies, the requirement of their categorisations based on successful applications have become essential. Therefore, the

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first objective of this paper is to categorise the technologies of image segmentation by conceptualising the implementation details. Image segmentation techniques which are applied on optical remote sensing image segmentation are included whereas those applied on active remote sensing satellite imagery like SAR imagery are excluded because of the reason already mentioned. However, in order to state the technological development some of the non-remote sensing applications are stated too. The second objective of this paper is to give an insight to the readers about the state of art of technological aspects of image segmentation and aid in deciding the mathematical form for image segmentation.

The rest of the paper is organized as follows. Section 2 discusses about the development of segmentation as per the existing review papers on image segmentation. Section 3 describes the categorisation of image segmentation from broad to fine level. Section 4 states the conclusion of the performed review. In order to state the development in a particular technology, similar methods are grouped and presented in a paragraph in rest of this literature.

2. DEVELOPMENT OF SEGMENTATION

One of the early application of image segmentation on remote sensing points to ECHO (Extraction and Classification of Homogeneous objects) classification by Kettig and Landgrebe (1976). This states that association of segmentation with remote sensing imagery was not much later than the operation of the first remote sensing satellite Landsat-1 in 1972. There have been many developments in remote sensing image processing techniques after that. Haralick and Shapiro (1985), Reed and Buf (1993), Spirkovska (1993) and Pal and Pal (1993) did extensive review on early stage of image segmentation techniques existed used in various applications along with remote sensing. Developments of image segmentation algorithms for remote sensing imageries have been drastically increased after the availability of high resolution imagery (Schiewe, 2002; Blaschke, 2010). This is obvious with the failure of pixel based techniques on high resolution imageries as discussed in the introduction section. Further, the commercially available software eCognition, since 2000 based on Fractal Net Evaluation Approach (FNEA), incorporating similarity of objects at hierarchical scale, has revolutionised the research on image segmentation and is still influencing the research very substantially (Baatz and Schäpe, 2000; Blaschke, 2010). This is why most of the review papers before the period of the year 2000 don’t specifically cover remote sensing applications. After that we do have a few good review papers. For example, Schiewe (2002) categorised the available remote sensing technologies for high resolution imagery, Carleer et al. (2005) evaluated qualitatively some of the most widely used image segmentation technologies for very high spatial resolution satellite imagery, Shankar (2007) presented various techniques with mathematical details of image segmentation techniques and Blaschke (2010) on OBIA.

3. CATEGORISATION OF SEGMENTATION

The abundance of literature on image segmentation makes the categorisation both necessary and challenging. The approach of categorisation in this paper is supplementary to some earlier review papers mentioned in section 2. (Reed and Buf, 1993; Pal & Pal 1993; Spirkovska, 1993; Schiewe, 2002; Shankar, 2007). Most of the earlier literatures have categorised them as a) Edge based b) Point/Pixel based c) Region based and d) Hybrid approach. Guo et al. (2005) categorised them as colour based and texture based algorithms. However, a more clear delineation is required considering the techniques which are used to achieve segmented objects.

A more general method of categorisation based on approach towards image analysis and applicable even beyond image segmentation domain are the bottom-up and top-down approaches. In image segmentation domain, they are often stated as model driven (top-down) and image driven approach (bottom-up) (Guindon, 1997). In this paper, this approach is stated as first stage of categorisation. It can also be stated as segmentation control based categorisation. However, in eCognition/Definiens developer software top-down and bottom-up approach refers to hierarchy of segmentation (eCognition Elements User Guide, 2004). It can be said that bottom-up approach forms object by combining/merging pixels or group of pixels whereas top-down approach moves from splitting the whole image into image objects based on heterogeneity criteria (Benz et al., 2004). However, this is not the only definition.

The second stage of categorisation points to features or homogeneity measures based approaches used to delineate image objects. The third stage of categorisation is based on operations on image used to generate image objects. These are edge detection, region growing/splitting and may be both of them. It is important to note that these stages are highly interrelated and generally developed methods pick up one or more methods from the list at different stages to perform final segmentation. For example, Beveridge et al. (1989) used thresholding object/background model for generating initial regions and region merging algorithm with spectral, shape and connectivity as homogeneity measures. Tilton (1996) used both region growing and edge detection for Landsat TM data. A detailed description of the categorisations and their inter-relationships are stated in the subsequent sections. Apart from aforementioned categorisation, image segmentation can also have supervised and unsupervised approach. Unsupervised segmentation holds its proximity to feature extraction and clustering whereas supervised segmentation incorporates segmentation accuracy as an addition to unsupervised scheme.

3.1 Image Driven approach

Image driven approach operates directly on the image pixels and detects objects solely based on the image features (Maxwell, 2005). Image driven approach extracts object based on the statistical features of the image derived from the pixels. This includes most of the solely edge based segmentation techniques. Edge based techniques detects edges and then closes the regions by contour generating algorithms (Schiewe, 2002). Canny Deriche operator is considered as good edge detector for remote sensing purposes (Carleer et al. 2005). However, different algorithms can also be tried. For example, Chehdi et al. (1993) used zero crossing of second derivative along four major directions to detect edge points and consequent closing of edges to generate regions of SPOT image. Edge detection is now more used for feature extraction in remote sensing and in segmentation of medical imagery (Pham et al., 2000). However, watershed transform is the current edge based segmentation technique being utilised in segmentation (Carleer et al., 2005).

3.2 Model Driven approach

Model based approach assumes that objects in an image are present in a certain pattern. Interested readers can look into

Rosenfield and Davis (1979) for more understanding of image models and segmentation. A list of models generally used for image segmentation are a) Object Background/Threshold Model, b) Neural Model, c) Markov Random Field Model, d) Fuzzy Model, e) Fractal Model, f) Multi-resolution and g) Transformation model namely Watershed model and Wavelet model. MRF model, Fuzzy model, Fractal model and Neural model have been widely studied previously (Pal and Pal, 1993; Reed and Buf, 1993). Therefore, the newly developed model comprises Watershed model and multi-resolution model. Fractal model has not much significant application in remote sensing and wavelet model is inherited in multi-resolution model. Hence, except fractal model all the models and their developments, approaches and applicability are described in subsequent sub-sections.

3.2.1 Object-background Model: Object Background models are based on histogram thresholding. They are primitive models for image segmentation. They follow a concept that there is a uniform background and objects are irregularly placed on this background (Rosenfield and Davis, 1979). They are mainly based on spectral properties. Spectral variation is represented by image histogram. This makes image histogram the choice for object delineation. Hence, finding an appropriate threshold between object and background fulfils the task of object identification. Most of the threshold based method follows an image model. In the next paragraph, some of them are discussed.

The widely used bi-level thresholding techniques have underlying object and background modelling (Weszka, 1978). Threshold can also be calculated based on the maximisation of class (object and background) separability error/ discriminant analysis (Otsu, 1979), maximisation of entropy based on the assumed probability distribution model (Pal and Pal, 1991) and many more. A detailed review on thresholding techniques can be found in Sahoo et al. (1988). Fuzzy thresholding approaches are the current developments in this field (details in fuzzy model section).

Currently, thresholding based methods are not popular in remote sensing areas especially in urban remote sensing applications with high resolution imagery. This is because of high degree of variation of histogram and hidden clustering problem (Beveridge et al., 1989).

3.2.2 Markov Random Field Model: Markov random field (MRF) model is not so old in remote sensing applications as compared to histogram thresholding. MRF model was conceptualised from Ising model (pp.1-23, Kinderman and Snell, 1980). MRF model takes into account the neighbourhood relationship which makes it attractive for modelling texture and contexture of images. The detailed mathematics of types of MRF models and their estimations can be found in the book by Li (pp. 21-47, 2009). However, a short summary of applications on remote sensing image segmentation is presented here.

One of the seminal papers of MRF in segmentation is Hansen and Elliot (1982). In remote sensing, the application of MRF was much later by Jeon and Landgrebe (1992). They used MRF for contextual classification of Landsat TM temporal data (pp. 243, Richards and Jia, 2006). Bouman and Shapiro (1994) applied unsupervised segmentation scheme with modified MRF model and named the model as multi-scale random field model (MSRF). MSRF used hybrid structure of quadtree and pyramid graph for scale representation. Then, expectation maximisation (EM) algorithm used for solving sequential maximizing a posteriori (SMAP) whose solution calculates the required parameters of MSRF model. They used multispectral SPOT image for their experimental results. Spectral and spatial features were used in MSRF model. Raghu and Yegnarayana, (1996) used supervised scheme for segmentation. They applied Gabor filters, for extracting texture feature, constituting a multi-resolution feature extraction mechanism. Texture feature vector was represented as Gaussian distribution and a posteriori probability scheme was formulated for assigning a partition label to a pixel where partition is expressed as noncausal MRF. Posterior probability of segmentation model was represented as Gibbs distribution and maximizing a posterior probability was done using Hopfield neural network with a deterministic relaxation modelling. This process used spectral, texture, spatial and prior knowledge as prior distribution. Technique was tested on three band image of IRS satellite. This paper used spectral, spatial and texture, in form of local interactions and class information. Both of the above method has used multi-resolution concept (see section 3.2.5). Jung et al. (2005) used multi-resolution MRF based unsupervised texture segmentation using Discrete Wavelet Transform (DWT). A MRF model was applied on each sub-band image separately, obtained from DWT considering spatial adjacency relationship. Parameter estimation was done by least squares estimate of Pseudo-maximum Likelihood. MAP criterion was optimized using simulated annealing (SA). Landsat TM was used for generating results through Gaussian MRFs. The properties used are spectral, spatial, contextual (spatial adjacency rule and clique functions) and texture.

Tsai and Tseng (1997) developed unsupervised segmentation scheme in which RGB of SPOT satellite was transformed into HSI colour space to estimate the number of colour sets by scale space filter based histogram thresholding. Then, iterated conditional mode (ICM) algorithm was employed for MAP estimation of GMRF based pixel partition labelling. Method used spectral and spatial information using texture (hybrid of local and global texture information) features for pixel based segmentation. Tseng and Lai (1999) also used GMRF but approximation was done by using Genetic algorithm instead of ICM for MAP estimation.

Sarkar et al. (2000) developed a modified technique to reduce the complexity of MAP-MRF estimation. Instead of working directly on pixels, they used a two stage algorithm for over-segmented image. At first stage, region adjacency graph was plotted for those regions. Energy function of MRF model was defined based on intra-region homogeneity and inter-region dissimilarity. At second stage, region merging is performed based on these energy equations value compared with a threshold based on Fischer distribution. This is an unsupervised MRF model based region merging approach which utilised spectral, spatial and textural properties. Sarkar et al. (2002) extended the above mentioned MRF based unsupervised segmentation approach for multiband imagery and used it for land-use classification.

D'Elia et al. (2003) modified Tree structured MRF model based on binary split of the image regions at each step. Initially, the regions were split in a binary tree pattern based on splitting criterion. In order to reduce fragmentation, estimation of field parameters was locally adaptive and a region merging parameter was also included. They modelled the image as a linear combination of original value plus zero-mean Gaussian noise. Estimation of the field parameters were based on local neighbourhood characteristics using maximum pseudo-likelihood estimation. Finally, MRF labelling was performed using MAP estimation through iterative conditional mode approximation technique. Poggi et al. (2005) used the Tree-structured MRF model for supervised texture segmentation on multi-spectral spot data which uses prior knowledge about the class and its estimated parameters.

In some other segmentation applications, Yang et al. (2008) used MRF in fusion based segmentation of SAR and Landsat imagery. They used region adjacency graph for MRF model and region reliability measure based on image properties for fusion. Moser and Serpico (2008) used graph based multiscale segmentation and fused the feature of those segmentations at coarse and fine scales to get final segmentation.

MRF models have attracted quite a decent amount of research for image segmentation. This is because of its ability to integrate spectral, textural, contextual, spatial properties of image and even prior knowledge in form of prior distribution. However, the mathematical formulation and high computational complexity are the drawbacks.

3.2.3 Fuzzy Model: Fuzzy theory had been conceptualised by Zadeh (1965). It has been applied in various fields of engineering applications. Fuzzy segmentation adds fuzzy boundary for objects. In the subsequent paragraphs, few developments and fuzzy logic based techniques applied in remote sensing image segmentation would be stated.

In early remote sensing, fuzzy segmentation was derived from clustering methodology. In order to be tuned with the terminologies of research papers, clusters and segments are used interchangeably in this literature. Cannon et al. (1986) utilised fuzzy c-means clustering for image segmentation. Fuzzy c-means clustering is a form of minimizing within group sum of squared (WGSS) error. Each pixel holds a membership value derived from local minimum of WGSS error. Two methods used for hard clustering was confusion matrix oriented merging (percentage of total pixels in that cluster) and minimal spanning tree merging whose nodes are cluster centres and edges are distance between cluster centre. Here, the class information was already available which helped in pruning the spanning tree to form segments. Krishnapuram and Kellel (1993) modified fuzzy c-means by possibilistic c-means. They introduced a scale parameter to modify the objective function of original fuzzy c-means. This method doesn't the need of stating the number of clusters beforehand and is robust even in the presence of noise and outliers. Hence, filtering step may be avoided. However, this method requires a reasonable scale parameter value and good initialization. Thus, restricts its capability of automated segmentation. Fan et al. (2009) proposed a single point iterative weighted fuzzy c-means which uses prior knowledge for initialising cluster centres and spatial and spectral information for weighing the original fuzzy c-means distance calculation.

Caillol et al. (1993) incorporated fuzzy sets in Gaussian Markov random field model to segment image. They introduced an interesting approach in the sense that their method incorporates both hard and fuzzy segmentation simultaneously. They named their method as fuzzy stochastic estimation maximization. However, their approach was limited to two class segmentation. They primarily used grey level values. Tzafestas and Raptis (2000) used an iterative fuzzy clustering which can incorporate image properties namely, spectral, spatial, texture and frequency in fuzzy form for segmentation. The algorithm applied is locally adaptive and number of output clusters/segments is not fixed a priori. Thus, it produces optimum number of segments till it reaches a predefined threshold.

Pal et al. (2000) used fuzzy techniques for histogram thresholding based segmentation. They used fuzzy entropy, fuzzy geometry, fuzzy correlation and fuzzy clustering techniques for thresholding. Results were demonstrated on IRS and SPOT satellite imagery. Bandyopadhyay (2005) used genetic algorithm for fuzzy clustering. He included spatial information by incrementing pixel vector with mean of a 3x3 or higher neighbourhood. Then, spatial information was included using up-down pixel value difference from centre pixel. Wuest and Zhang (2009) have modified the Hierarchical Split and merge algorithm (HSMR) to perform an unsupervised segmentation. They used fuzzy band ratio to describe regions by their class densities. Then, fuzzy logic was used for comparing the region similarity. The algorithm was applied on Quickbird imagery and segmentation is basically proposed for land use purposes.

Most of the fuzzy segmentation methods are derived from fuzzy c-means clustering and fuzzy thresholding (Shankar, 2007). However, it is possible to incorporate fuzzy model in the most of the existing segmentation model e.g. Fuzzy MRF stated here and Fuzzy Neural models to be stated in next section. The decision of incorporating fuzzy model is based on the achievable complexity level of the segmentation.

3.2.4 Neural Model: Neural networks are based on simulation of human brain processing element called as Neurons. The structure of a neuron is shown in the fig-1. Rectangular blocks correspond to input multiplied by weights (W_i) and F correspond to threshold function and z correspond to linear sum of weights multiplied with corresponding input. One can build a network by increasing the number of neurons and number of layers or outputs, adding elliptical blocks in horizontal and vertical fashion. Layers in between input and output layers are known as hidden layers. The basis of Neural network lies in training of neural network. The aim of training is to model the process of data generation such that it can predict the output for unforeseen data. Training is generally associated with supervised methodology. However, unsupervised network can also be formulated e.g. Adaptive Resonance Theory 1 (ART1), ART2, Fuzzy ART and Self-organizing Maps (pp. 102-147, Tso and Mather, 2001).

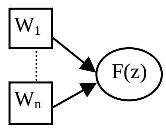

Figure 1. showing structure of a neuron

One of the early applications of neural networks in image segmentation is by Visa et al. (1991). They used co-occurrence matrix based texture feature vectors as input to self-organizing map (SOM) neural networks. Their aim was cloud detection from NOAA-10 and NOAA-11 satellite imagery. They used texture features derived from spectral values. Solaiman et al. (1994) proposed an edge based segmentation by automatically tuning parameters of Canny-Deriche recursive filtering using a multi-layer perceptron (MLP) network. They utilised spectral and spatial properties. Chen et al. (1996) modified the learning technique of MLP network by first removing any hidden layer, then selecting a polynomial basis function as the activation function. Essentially the network was linearized by this modification. This linearization made it capable of being trained by a Kalman filtering technique. This reduced the training time compared to back-propagation training. This is essentially a supervised technique because of MLP network. The process is based on intensity values or spectral properties.

Baraldi and Parmiggiani (1995) modified ART neural network to simplified ART neural network (SARTNN) such that it estimates much lesser user defined parameters than ART and also has capability to accept multi-valued input. The architecture is similar to ART and used Vector degree of Match (VDM) for comparison of multi-valued vector. This process doesn't require a priori number of processing elements. They applied the algorithm for clustering the Landsat-5 imagery and found better clustering. Chen et al. (1997) proposed a neuro-fuzzy scheme for image segmentation. In the first step, they transformed image using histogram based non-uniform coarse coding technique. This resolved the proportion ambiguity, observed with patterns having proportional relationships when used as input for ART, due to normalizing inputs. In the second step, ART2 was applied as neural network due to its unsupervised nature. This clustered the input pattern into the desirable number of classes. However, the final informative classes are still to be formed. This final step was performed using fuzzy clustering. This method used spectral and spatial information in the form that the probability that adjacent pixels belong to same class is large. This method was applied on three multispectral channels, Green, Red and Infrared of SPOT HRV sensor.

Kuntimad and Ranganath (1999) used Pulse coupled neural network (PCNN) for image segmentation. The essential feature of PCNN lies in its one to one correspondence to image pixels. Further, it requires no training and directly produces segmented objects with edges. PCNN has also capability to utilise the neighbourhood relationship. Li et al. (2007) used improved pulse coupled network for image segmentation of IKONOS imagery. Their modifications differ in the sense of linking of neurons, edge-preserved prior smoothing instead of just smoothing and reduce algorithm complexity.

ANN might not have caught the eyes of researchers of remote sensing image segmentation but it has wide applications in medical imagery with different type of ANN like SOM, MLP and Hopfield Network to name a few (Peterson et al., 2002). This may be due to the challenge of generalization in conventional neural networks (Atkinson and Tatnall, 1997). However, PCNN seems to be a promising approach for unsupervised image segmentation with its capability to incorporate neighbourhood relationship. This area needs further research.

3.2.5 Multi-resolution Model: Woodcock and Strahler (1987) stated the importance of factor of scale in identification of objects present in the remote sensing imagery. Scale of an object is stated as level of aggregation and abstraction at which an object can be described (Benz et al, 2004). An object which is smaller than the spatial resolution of image cannot be identified. It is because of inappropriate scale of object. Based on this, two problems can be stated. Firstly, if object size is large then high spatial resolution satellite would fragment the object and secondly, if object size is small then low spatial resolution may not even recognize it. With the availability of high resolution satellite imagery second problem has been eliminated. Now, the first problem is to be solved. A general idea of multiscale/multiresolution approach arose for solving this kind of problem. Multi-scale segmentation can go both ways from coarse to fine (top-down) and fine to coarse (bottom-up) (Zhong et al., 2005). The idea for coarse to fine level states that initial segmentation can be performed at coarse level and this initial segmentation acts as input to next finer level segmentation. The reverse is true for fine to coarse approach. However, in both approaches a threshold is defined to decide merging or splitting. This creates a hierarchical segmentation. Now the next concern is how to represent the multi-resolution/multiscale/hierarchical and segment based on this representation scheme. This is the topic of discussion in the next paragraph.

Bongiovanni et al. (1993) used pyramidal structure for multi-resolution segmentation. They assumed image to be bi-modal and based on spectral property a threshold is determined to assign bimodality. The method iteratively finds the bi-modality and then follows top-down approach to segment based on their bimodality. The representation scheme for this operation was pyramidal where each pyramid node had four children. Bouman and Shapiro (1994) applied multiscale representation using a hybrid of pyramid graph (at finer level) and quadtree (at coarse level) for a MRF based image segmentation (already described in sec. 3.2.2).

Baatz and Schäpe (2000) brought significant development in the research of multi-resolution segmentation for remote sensing imagery after the introduction of Multi-resolution/hierarchical segmentation using Fractal Net Evaluation approach (FNEA). FNEA represents the notion of hierarchy as fractal net because of the self similarity notion of fractals. Each coarser level gets the input from finer level and if an object is identified at coarser level then it repeats its representation at each finer level which is referred as similarity. The process starts with each pixel as objects and then subsequently merged based on the criteria in which merged region shouldn't exceed a defined heterogeneity threshold. This approach has capability to incorporate spectral, texture, spatial, shape, size, prior knowledge and contextual properties of image. This approach is incorporated in eCognition/Definiens Developer, a commercial software product. This software revolutionised the field of remote sensing image segmentation with its immense possibility to provide GIS ready information (Blaschke, 2010; Benz et al., 2004). The selection of parameters, scale, smoothness and compactness, for multi-resolution segmentation requires an expert knowledge which makes it semi-automatic. However, Maxwell and Zhang (2005) proposed a fuzzy approach which automatically selects the parameter of the segmentation used in multi-resolution approach.

Apart from the development of eCognition/Definiens Developer some other techniques are also developed. Chen et al. (2003) applied a top-down strategy for multiscale segmentation applied on SPOT HRV image. They performed discrete wavelet transform on first principal component, obtained from PCT of original bands, to obtain coarse scale image and applied clustering for coarse scale segmentation. Segmentation at fine scale used region growing procedure based on seed pixel of region. Pixels are grouped with seed pixel based on spectral and textural feature vector. Grouping is based on a threshold of acceptable heterogeneity after merging. This process is performed iteratively until all coarse scale segmentation was subjected to fine scale segmentation. Zhong et al. (2005) used a bottom–up approach for multi-scale segmentation on IKONOS image using. Starting with a pixel region, region is subsequently merged with other based on achieved homogeneity measure. Homogeneity measure is derived from colour feature, smoothness feature and compactness feature. Once, every region at a particular scale are processed like this, the average size of objects are calculated. If average size satisfies the size threshold then segmentation is optimal otherwise segmentation is carried on with the achieved regions.

Li et al. (2008) applied multiscale segmentation using hybrid of statistical region merging (SRM) for initial segmentation and minimum heterogeneity rule (MHR) for merging objects for high resolution Quickbird imagery. SRM utilises spectral, scale and shape measures for initial segmentation. Segmentation using SRM follows region growing technique where region growing is based on statistical test. Minimum Heterogeneity rule used colour (spectral) and shape property for region merging.

Multi-resolution model is indeed the most sought after technique for remote sensing image segmentation. It is possible to combine the concept of multi-scale to any other segmentation approach e.g. with MRF model (Bouman and Shapiro, 1994). Its combination with watershed model will be defined in next sub-section. Its success lies in its capability to incorporate spectral, shape, size, texture and contexture features of region at various scales for efficient segmentation especially for high resolution complex landscape imageries. The most typical part of this model is appropriate scale representation and information extraction from them (Chen et al., 2009). The method developed by Chen et al. (2009) aids in identifying the scale of proper representation of objects.

3.2.6 Watershed Model: Watershed model is a mathematical morphological approach and derives its analogy from a real life flood situation (Beucher, 1992). It transforms image into a gradient image. Then, image is seen as a topographical surface where grey values are deemed as elevation of the surface at that location. Then, flooding process starts in which water effuses out of the minimum grey value. When flooding across two minimum converges then a dam is built to identify the boundary across them. This method is essentially an edge based technique (Carleer et al., 2005). The original watershed algorithm was susceptible to over-segmentation so a modified marker-controlled based watershed algorithm was proposed by Beucher (1992). Watershed algorithm produces over-segmentation because of noise or textured patterns. The application of watershed algorithm on remote sensing imageries is relatively recent than other models. Next few paragraphs describe several modifications on marker-controlled watershed algorithm to reduce over-segmentation problem.

Traditionally watershed algorithm was applied with median filter to eliminate noise and preserve contours (Carleer et al., 2005; Sun and He, 2008). Chen et al. (2006) stated that median filter fails to encounter high imagery texture, generally present in high resolution imagery. They proposed a modified technique to encounter this problem. They used a non-linear filter named Peer group filtering for removal of noise and image smoothing. Then, a floating point based rainfall algorithm for watershed transformation was applied for initial segmentation. Then, a multi-scale region merging algorithm was applied based on spectral, shape and compactness feature for final segmentation. The algorithm was applied on IKONOS imagery. Chen et al. (2008) proposed a different gradient operator for watershed transform which efficiently reflect texture information. The gradient image used is known as Homogeneity gradient image or H-image. H-values are calculated by a local window based operation. Dark and bright areas in H-image represent region centers and region boundaries. A rainfalling algorithm for watershed transformation was used followed by region merging, where regions were represented using Region adjacency graph. Region merging was based on colour, texture and shape features. Algorithm was applied on SPOT three band image with 2.5 m resolution.

Watershed algorithm is new segmentation approach with relatively less application in remote sensing image segmentation than other described models. However, it may be good for initial segmentation in a multi-scale resolution as it produces an over-segmentation. Over-segmentation elimination is also a problem associated with this method which needs further research. The commercial software ERDAS Imagine Extension (IMAGINE WS) has incorporated this algorithm.

3.3 Categorisation based on homogeneity measure

Next stage of categorization corresponds to the homogeneity measures used for image segmentation. But before that it is necessary to determine the possible homogeneity measures of image features. This requires a well understanding of image objects and the final outcome of image segmentation. Image objects are real world objects represented on remote sensing image. With very high resolution satellite, image objects can be visualized by human eye. This has been addressed by some researchers. For example, Wang and Terman (1997) suggested sensory cues of segregation based on Gestalt psychology for segmentation and Fu and Mui (1981) as psycho physical perception problem for segmentation. It is similar to elements of analysis for image interpretation by human eye (pp. 67-68, Richards and Jia, 2006). Thus, the possible measures are based on similarity comprises spectral, texture, spatial, size, shape, and temporal. Some other semantic information prior knowledge, context and connectedness are also required (Wang and Terman, 1997).

The primary homogeneity measure is spectral/tonal feature. Secondary homogeneity measures are spatial, texture, shape and size. Tertiary homogeneity measures are contextual, temporal and prior knowledge (pp. 67-68, Richards and Jia, 2006). As per the order, the most important is primary then secondary and then tertiary. Secondary and tertiary measures are more important when the boundaries of objects are required to be precise with very less mis-segmented pixels. In this study, more emphasis is given on secondary and tertiary measures which were not widely covered in earlier literatures. The list of measure may not be exhaustive but surely cover most of the available techniques existing for image segmentation. Subsequent sections describe the trend of techniques for different homogeneity measures used in image segmentation.

3.3.1 Spectral and Textural Features: The most primitive measures of homogeneity are spectral and textural features. Spectral values refer to grey levels or pixel values of an image. It has been long realised that using only spectral features good segmentation results are not possible but was still practiced due to the ease of incorporating them in digital format (Kettig and Landgrebe, 1976). Texture features points to spatial pattern represented by spectral values (Haralick et al., 1973). A textured image may have various texture patterns. However, quantitatively characterizing texture is not simple (pp. 128-130, Richards and Jia, 2006). Due to this fact texture segmentation has been studied widely generally in combination with other features like shape, spectral and contextual and various models till today.

Chen and Pavlidis (1978) used co-occurrence matrix and a quadtree based structure to determine texture similarity for grouping pixels in a region. Cross et al. (1988) also used quadtree based hierarchical structure and applied texture measure was local difference statistics. Guo et al. (2005) used texture measure derived from local binary pattern and used wavelet transform to pre-process the image and derived texture from local binary pattern. They also used quadtree structure for splitting and merging. It can be seen from trend that quadtree based hierarchical image splitting has been the trusted method of texture segmentation for decades.

Conners et al. (1984) used spatial grey level dependence method (SGLDM) and six texture measures namely inertia, cluster shade, cluster prominence, local homogeneity, energy and entropy in region growing algorithm based on split and merge tecnique. Ramstein and Raffy (1989) used variogram and fractal dimension measures for texture segmentation and classification. Ryherd and Woodcock (1996) used a 3x3 adaptive window to calculate texture image based on local variance and applied a multi-pass region growing algorithm which builds spatial homogeneous objects using Euclidean distance in n-dimensional space. They showed that segmentation accuracy of derived texture image is better when compared with original image, used spectral property only. Algorthm was tested with SPOT panchromatic image.

Texture segmentation is one of the most sought after segmentation technique. It is evident from Reed and Buf (1993) and the above literature. This is mainly because of the presence of highly textured regions in high resolution satellite imagery. Currently, the research has shifted from texture to multi-resolution model.

3.3.2 Shape and Size Features: The importance of shape and size measure could be understood when the natural object are to be identified on satellite imagery. For example, a river and a pond may has same spectral, texture and spatial properties but they differ in shape and size. It is because rivers are linear and unbounded features whereas ponds are non-linear and bounded features. Shape and size measures are mostly utilised as complementary to each other. Further, they are always applied in conjunction with the spectral and texture measures. Only some substantial algorithms based on the recent developments are mentioned.

Beveridge et al. (1989), performed over-segmentation and then utilised shape, connectivity and size measure for region merging to achieve segmentation. Multi-resolution models represent the size of object through spatial scales (Bongiavanni et al., 1993). Fractal Net Evaluation approach (explained in section 3.2.5) used in commercial software, eCognition/Definiens developer, also uses scale, shape and compactness parameter.

The state of art use of shape and size refers to multi-scale/multi-resolution approach to image segmentation. Shape and size measures are especially helpful when delineating complex objects in high resolution satellite imagery.

3.3.3 Context: Context generally refers to spatial context which means relationship of pixels with its neighbourhood (Thakur and Dikshit, 1997). Contextual information is also used in conjugation with spectral or texture or both measures. Few methods are found which utilise specifically context based segmentation. Context helps in avoiding fragmentation of a segment and merging. For example in an urban image, cars in a parking lot may cause fragmentation unless context measures are applied.

A good recent example of context based segmentation is Fan and Xia (2001). They deduced context information from spatial and scale space of image and modeled five context models with quadtree model for scale dependency. They called their algorithm as multi-contextual (due to five context models) and multi-scale approach to Bayesian segmentation which in mathematical terms solves context-based mixture model likelihood. They used their methods for aerial and SAR imagery. Even eCognition/Definiens Developer software has the capability of including the context information based on neighbourhood relationship measures. Benz et al. (2004) demonstrates in the paper that how eCognition integrates spatial and scale context as semantic information in identifying the appropriate image objects. Contextual constraints are used in segmentation and classification and are well modeled by Markov Random Field. This is why several context-based classifications use MRF model (Melgani and Serpico, 2003; Jackson and Landgrebe, 2002).

Context is especially useful when segmentation requires bigger area to be identified as one segment e.g. land use classification. MRF models are currently the best model for implementation of contextual measures.

3.3.4 Temporal: Temporal measure refers to measurement based on images of same area and sensor characteristics in different time (pp. 67-68, Richards and Jia, 2006). Temporal measure is not directly used for segmentation but is used as an application of segmented image.

Carlotto (1997) performed temporal segmentation for change detection from Landsat TM. He used total difference image to segment based on histogram thresholding. Jeansoulin et al. (1981) performed segmentation using fuzzy edge detection and region growing for segmentation and demonstrated how temporal criterion can be used to detect changes based on objects. Hanaizumi et al. (1991) used spatial segmentation for change detection and showed result on Landsat TM imagery. They used division and detection procedure where divison/region-splitting was performed by fitting regression model on pixel scattergram. Dambra et al. (1991) fused multi-temporal imagery using segmented image. SAR segmented image is also used for change detection. Several SAR segmenting methods are reviewed by Caves et al. (1996).

Yamamoto et al. (2001) detected change in SPOT HRV and Landsat TM image using 3-D segmentation with time as Z axis. They applied local statistical regression model for region splitting using spatial and spectral measures. Hall and Hay (2003) used multi-object scale analysis for change detection which utilises Marker Controlled watershed segmentation (Beucher, 1992). Lhermitte et al. (2008) introduced multi-temporal hierarchical image segmentation. They segmented the 10 daily data of SPOT VGT sensor by first decomposing original image time series in Fast Fourier Transform component and then performed hierarchical segmentation analogous to eCognition (Baatz and Schäpe, 2000) using Euclidean distance between FFT components of same frequency as measure of similarity.

Temporal characteristics have important application in monitoring changes like land-use change, disaster mapping, traffic flows, crop mapping etc (pp-280-81, Campbell, 2007). Temporal segmentation has been used mainly for change detection in a series of temporal image. Its application is mainly seen for large area change detection rather than small area. Thus, more applications have been found on low resolution images than high resolution.

3.3.5 Prior Knowledge: Prior knowledge refers to photointerpreter knowledge regarding the regions/objects of the image (pp. 342-352, Richards and Jia, 2006). It may be the knowledge of classes of the image region or about some specific area, building or trends etc. Incorporating prior knowledge in image analysis is one steps towards developing artificial intelligence in the machine (Srinivasan and Richards, 1993). Prior knowledge may not be the primary measure for segmentation but it has the capability of utilising the location based information. For example, it is our prior knowledge which generally says that small buildings mean residential areas and large buildings means commercial or institutional areas. This indicates towards differentiation based on shape properties. In the next paragraph, few prior knowledge based segmentation or prior knowledge based homogeneity measure derivation are described.

Ton et al. (1991) divided segmentation techniques into two types as partial segmentation (without using a priori knowledge) and complete segmentation (using a priori knowledge). The approach for knowledge based can be further divided into histogram-oriented and cluster-oriented (Ton et al., 1991; Paudyal et al., 1994). Most of the popular method like Hierarchical split and Merge (Ojala and Pietikainen, 1999), region growing, multi-resolution used by eCognition (Baatz and Schäpe, 2000) etc are partial segmentation techniques. Ton et al. (1991) used spectral and spatial knowledge rules for supervised segmentation of Landsat TM image. They automated generation of spectral knowledge based rules based on training data and hierarchical classification. They applied both threshold and region growing for segmentation.

Liu et al. (1993) used texture measure for region uniformity and contexture information at pixel level for segmentation. They used knowledge in determining the best texture measure, which gives minimum error using multivariate Gaussian Bayesian classifier, out of the available for good segmentation. The method used is essentially supervised segmentation. Using similar concepts some researchers incorporated knowledge in textural measures (Paudyal et al., 1994; Simman, 1997).

Smits and Annoni (1999) used no prior information but derived knowledge, automatically from a selected region, to select the best feature which can distinguish object from its neighbours. Jinghui et al. (2004) also used GIS prior information to extract building from Quickbird imagery using fuzzy connectedness algorithm.

Poggi et al. (2005) used tree structured MRF model in incorporating prior knowledge for supervised segmentation. Benz et al. (2004) also showed how expert knowledge can be included in segmentation based fuzzy classification.

Prior knowledge is incorporated in mathematical models by using class distribution information. In fuzzy models, it can be incorporated as semantic rules (Benz et al., 2004). Prior knowledge is specifically useful when for segmentation of complex landscape object indistinguishable using texture and context.

4. CONCLUSIONS

With the numerous amounts of image segmentation techniques presented in this paper, it might be possible to get confused regarding what is presented in this paper. Thus, it is important to summarize all of those to regain the content of this paper.

Image segmentation methodologies were categorized in three stages. At first stage comes model driven approach and image driven approach (mainly based on statistical analysis). The second stage corresponds to homogeneity based measure, and final category corresponds to mode of operations on an image, e.g. edge detection, region growing/splitting.

In model driven approach, object background model is insufficient for remotely sensed imagery. Neural model generally suffers from complexity regarding decision of network structure, proper learning and generalization of network. Hence, neural model is not one of the liked approaches by most of the researchers. Markov Random Field model has attracted quite a decent research in image segmentation. It can utilise significant image properties namely, spectral, spatial, texture, contexture and prior knowledge. However, MRF lacks the integration of shape and size and implementation of MRF is very complex.

Fuzzy model has been applied in remote sensing image segmentation mostly by means of fuzzy clustering of image or fuzzy thresholding. The strength of fuzzy model lies in ambiguity resolution. It can easily ensemble itself with neural model, MRF model and also histogram thresholding (Chen et al., 1997; Caillol et al., 1993; Shankar, 2007).

Multi-resolution (MR)/Multi-scale model is the most widely used model in remote sensing image segmentation. It has also been incorporated in a commercial software eCognition/ Definiens Developer. This model is capable identify object and object features at its intrinsic scale which makes object extraction of various scales possible (Chen at al. 2009). The problem of MR approach is scale representation and information extraction from each scale. The idea of MR approach is complex but when appropriately implemented has wide usage especially in remote sensing satellite images dealing with urban areas.

Watershed model based on mathematical morphological operators is another budding technology with respect application in remote sensing image segmentation. Further, research on this approach is required.

Homogeneity measures described in this paper are spectral, spatial, texture, shape, size, contextual, temporal and prior knowledge. Spectral measure is the most primitive one and quite long it has been realised that this alone wouldn't be able to deal with high resolution satellite imagery (Zhong et al., 2005). The second most widely applied homogeneity measure is based on texture. Texture segmentation is more successful because it inherits spectral and spatial properties in itself. However, this would still not yield a perfect segmentation. A better segmentation would require a model or methodologies which utilise most of the above mentioned measures to calculate region homogeneity or heterogeneity threshold. Integration of prior knowledge and contextual information has seen quite a good research in segmentation.

The selection of segmentation approach depends on what quality of segmentation is required. Further, it also depends on what scale of information is required. Few examples, based on done literature review in this paper, would be stated now to illustrate the idea. For urban GIS applications objects at different scale are required. For landuse coarse scale segmentation is required whereas for land cover fine scale. Hence, multi-resolution model would be the best choice. For highly textured image MRF model might be the good choice.

Fuzzy model would be good choice to represent ambiguity of region boundaries. Neural model would be good choice no prior distribution can be assumed and not very high quality object information is required. Among homogeneity measures, spectral, shape, size, scale, compactness and texture should be concerned when complex landscapes are to be analyzed.

As a part of future recommendation, some of the mentioned approaches in this paper should be implemented to look how each behaves on same image. Behaviours with images of different spatial resolution would be quite interesting. Further, addition of existing quantitative analysis of recent segmentation evaluation techniques would be quite helpful.

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