Selecting Otimal RBF Kernel with Machine Learning for Feature Extraction and Classification in SAR Images

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Abstract
Kernel methods are gaining popularity in image processing applications. The accuracy of feature extraction and classification on image data for a given application is greatly influenced by the choice of kernel function and its associated parameters. As on today there existing no formal methods for selecting the kernel parameters. The objective of the paper is to apply machine learning techniques to arrive at suitable kernel parameters and improvise the accuracy of kernel based object classification problem. The graph cut method with Radial Basis function (RBF) is employed for image segmentation, by energy minimization technique. The region parameters are extracted and applied to machine learning algorithm along with RBF?s parameters. The region is classified to be man made or natural by the algorithm. Upon each iteration using supervised learning method the kernel parameters are adjusted to improve accuracy of classification. Simulation results based on Matlab are verified for Manmade classification for different sets of Synthetic Aperture RADAR (SAR) Images.

Index terms— machine learning; RBF kernel; image segmentation; graph cut kernel.

1 Introduction

utomatic identification and reporting of man-made structure in images is useful in several emerging applications including synthetic aperture RADAR (SAR) image analysis, robotic navigation, automatic surveillance, image indexing and retrieval etc. The paper given here focuses on the recognition of man-made structures, which can be categorized to have specific geometric characteristics. Mainly the application of automatic analysis on SAR images is considered here. The automatic man-made object recognition from SAR images is a non-trivial problem due to following reasons.

? The view from which the image is created can be limited in SAR category applications.

These factors make the computation of the image primitives such as junctions, angles etc., which rely on explicit edge or line detection, prone to errors.

In surveillance and military applications of SAR, Buildings and vehicles are the most important manmade structures, which need to be detected. Some of the previous work on detection of buildings is given at [6] [7][8] [9] and [10] on normal images. Large number of these techniques uses aerial images for building detection by generating a hypothesis on the presence of surface on building roof top image [6]. The first step is detecting low-level image characteristics such as edges and regions. In next step either geometric feature based hypothesis [7], or a statistical models such as Markov Random Field (MRF) [8] is applied. In [11] a technique was proposed to use graph spectral partitioning for detection. Several techniques used with normal image processing algorithms require complex mathematic operations on images and require noise-free images.

The work at [12] and [13] establishes method to classify the whole image as a landscape or an urban scene. Oliva and Torralba [12] obtain a low dimensional holistic representation of the scene using principal components of the power spectra. The power spectra based features to be noisy for SAR images, which contain a mixture of both the landscape and man-made regions within the same image.

The work at [13] uses the edge coherence histograms over the whole image for the scene classification, using edge pixels at different orientations. Olmos and Trucco [14] proposed a system to detect the presence of man-made objects in underwater images using properties of the contours.

The techniques discussed in [15][16] perform classification in outdoor images using color and texture features, with different classification schemes. These papers report poor performance on the classes containing man-made structures since color and texture features are not very informative for these classes [13]. However for SAR images these techniques cannot be applied. These techniques classify the whole image in a certain class assuming the image to be mainly containing either man-made or natural objects, which is not true for many real-world images. In case of SAR created images, the images are taken over wide area containing mixed real world and man-made objects. The figure 1, shows typical SAR image consisting man made objects.

2 Figure 1 : An S AR Created Image

In this paper, we propose to detect man-made structures in 2D images, formed by SAR. The proposed method uses Graph cut Image Segmentation method based on kernel mapping functions with machine learning algorithm on the SAR images. The section II illustrates introduction to kernel graph cut Image Segmentation principles and methods. The section III explains the various kernel mapping functions and machine learning algorithm simulated on the SAR images. The section IV has algorithm, simulation results and applications.

3 II.

4 Graph Cut Image Segmentation

The purpose of Image Segmentation is to divide an area into regions with a given description. Variational formulations partition an image to minimize an objective functional containing terms with descriptions of its regions and their boundaries. Continuous formulations view images as continuous functions over a continuous domain. The minimization function depends upon gradient descent. As a result, the algorithms converge to a local minimum; can be affected by the initialization. However these algorithms are typically slow and become a major hassle in applications which deal with large Images and thereby large regions.

The proposed functional consists of two terms: a kernel-induced term that measures the amount of deviation of the mapped Image data from piecewise constant linear data and regularization term which can be expressed as a function of region indices. The objective minimum functional is found by iterating through 2 steps via a common kernel function. Let ?? : r ? ?? ? ?? 2 ? ?? ?? = ??(??) ? ?? be an image function from a positional array ?? to a space F consisting of photometric variables such as intensity, disparities, color or texture vectors. F is segmented to ?? ?????? regions which finds a suitable partition in the discrete domain to find a region which is compatible with some of the image characteristics. Partitioning of the image domain ?? equals to assigning each pixel a label l in a finite set of labels L. A region ?? ?? is defined as the set of pixels whose label is l, i.e., ?? ?? = {?? ? ??|?? } is labeled . The purpose is to find the labeling which minimizes a given functional.

To calculate Segmentational functional , let ? be an indexing function. ? assigns each point of the image to a region.?:r ? ? ? ?(r) ? ?

where ? is the finite set of region indices whose cardinality is less than ?? ?????? . The Segmentation function can then be written as given in (**??**)S(?)= D(?)+ a R (?)

Where D is the data term and R is prior. ? is a positive factor.

5 b) Proposed Functional

Let ? (.) be a nonlinear mapping function from the observation space F to a higher dimensional feature Discrete formulations take images as discrete functions over a positional array. Graph cut Image Segmentation methods have been proved very efficient using this method. Minimi-zation by graph cuts provides a global optima and are less sensitive to.

The objective is to study kernel mapping to bring graph cut formulation for Multi region Segmentation of Images. The image data is implicitly mapped via a kernel function into data of a higher dimension so that the piecewise constant model, and becomes applicable. multiple regions. Each region is characterized by one label,?? ?? = {?? ? ?| ?(r) = l } ,1 ? ?? ? ?? ??????

Labeling that minimizes the functional in kernel induced space by graph cuts, as represented in (2).?? ?? ({?? ?? }, ??) = ? ? ???(?? ??) ? ??(?? ð ??"ð ??")? ?? + ?? ? ð ??"ð ??"({??,??}???? ??(??), ??(??))

ð ??"ð ??"???? ?? ?????? (2) Generally in machine learning algorithms, the kernel trick is to use a linear classifier map the the original nonlinear data into a higher dimensional space. The Mercer's theorem, states that any continuous, symmetric, positive semidefinite kernel function can be expressed as a dot product in a high-dimensional space, without knowing the mapping explicitly. We can use a kernel function, KF(x,y) for this mapping as given in (3).????(??, ??) = ð ?"ð ?"(??) ?? . ð ?"ð ?"(??), ?(??, ??)???? ??**(3)**

Where "." is the dot product in feature space. Therefore the Segmentation kernel function can be described as in (4). The functon J K is the non-ecludian distance in the original data space.({?? ?? }, ??) = ? ? ?? ?? (?? ?? + ???? ?? ?? ?????? ??) ? ð ??"ð ??"({??,??}???? ??(??), ??(??))**(4) c) Optimization**

The obtained segmentational functional is minimized with an iterative two-step optimization strategy. The first step consists of fixing the labeling and optimizing ?? ?? with respect to statistical regions parameters using fixed point computation. The second step consists of finding the optimal labeling/partition of the image, with the given region parameters provided by the first step, via graph cut iterations. The algorithm iterates these two steps until convergence. With each iteration ?? ?? is decreased with respect to a parameter.This guarantees the algorithm to converge to a local minimum.

6 d) Man-made object classification in SAR images

The Fig. 1, shows an SAR image created over a region consisting few manmade structures and trees. In several military applications it is very useful if there is an automatic way of identifying these objects. This section explains the proposed approach for machine learning (ML) on kernel based object classification on SAR images. The machine learning approaches can be divided into 3 major categories.

? Supervised learning: In supervised learning the input data along with actual output is used to train the machine learning algorithm. The ML algorithm iteratively arrives at optimal hypothesis by every time checking the algorithm output is correct or not. ? Unsupervised learning: Only the input data is given to ML algorithm. The ML algorithm need to cluster the points in feature space and further use statistical means to classify. The ML algorithm training data has no clue of the actual output. ? Reinforcement learning: In this case the actual output is not offered to ML algorithm, instead an indicative of (such as quality factor) correctness or failure is provided.

In this work the supervised learning approach is adopted, where the ML algorithm gets trained with the help of operator visually checking the SAR image. Even though other methods are possible, as a first step towards this classification problem, the supervised ML approach is adopted.

The Fig. 3 has the flow chart representation of implemented ML approach for binary classification of SAR image segments. The basic idea of kernel methods is to (?) transform the input data points (black dots) in to a highdimensional feature space, where they can be described by a linear model (straight solid line). The linear model found in feature space corresponds to a non-linear Selecting optimal RBF Kernel with machine learning for feature extraction and classification in SAR images model in the input space (curved solid line). The Fig. 4,

7 III. Kernel Based Methods for Object Classification

The unknown ideal target function is achieved through operator decision on each object of SAR image. The H hypothesis set consists of all pos-sible weight vectors. The selected hypothesis G is the final weight vector achieved after training. has the basic illustration of mapping involved in kernel functions.

This section describes the low level image parameters and mapped kernel functions which are considered for the ML algorithm. The edges, regions, statistical parameters are considered as input data set X. The output correct decision which is marked by operator is labeled as Y. Hence the training data set can be described as given in (5). ?? ? = (?? ?? , ?? ?? , ? ? ? , ?? ?? ?) ??(??) = ð ??”ð ??”ð ??”ð ??”??ð ??”ð ??” (?? ? ?? ??(??))**(9)**

Based on the sign the correctness is perceptron is used to update the weight vectors iteratively. The final selected hypothesis g becomes the candidate for classifying on the unknown data set.

8 ?? = {?} ?? ? ??

The Kernel function that is used here is Radial Basis function (RBF) kernel function which is a very

9 IV. Algorithm,Results And Applications

This section presents the results and discusses the possible applications of the developed ML lgorithm.

10 a) Algorithm

In the first step, regions are detected using Graph cut Image Segmentation method and pixel groups are made corresponding to each region.

In the second step the pixel coordinates are substituted in kernel mapping functions and feature space values are computed.

? To obtain region based classification, K means clustering algorithm is applied on the SAR Image to obtain clusters of the total image. ? Next on each cluster, Graph cut Image Segmentation algorithm is applied with specific kernel mapping function (RBF) to estimate the local minima convergence points. ? Contours are estimated over these points to finally obtain regions.?? = (?? ?? , ?? ?? , ? , ?? ??) ?? ? ?? = (?? ?? , ?? ?? , ? ? ? , ?? ?? ?) (?? ?? , ?? ??), (?? ?? , ?? ??), ? , (?? ?? , ?? ??)**(5)**

The Kernel functions considered here are first order and second order partial derivatives in the x and y directions. If the P being the pixel set for an edge the first order derivative can map the linear edges to constants. Similarly the second order derivative can map the circular manmade objects to constants. Let ?(.) be the mapping from the input data space to a higher dimensional feature/mapped space as given in (**??**) and (7).?? ?? , ?? ?? , ? , ?? ð ??”ð ??” ?? ? ?? ?? , ?? ?? , ? , ?? ð ??”ð ??”**(7)**

The first step in algorithm divides the image domain into multiple regions and edges (X). Each region is characterized by one identifier, Further the region characteristics are mapped to kernel function which becomes input to optimization algorithm.

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12 b) Simulation results

The ML algorithm with Graph cut Image Segmentation is implemented in MATLAB and simulation results of the same are discussed in this section. The Fig. 5, has the region detection output for a specific SAR image.

13 (a) (b)

The weight vectors for ML algorithm are biased to have reduced probability for target miss (P TM) at the cost of increased false alarm (P FA). This is because of obvious reason that the algorithm declared man-made objects will be further processed by operators or some other set of algorithms which can ignore if it is found to be not a region of interest. It is considered that, if an actual man-made object is not declared by ML algorithm, then its impact is high on the system operation. The Table I has the four possible scenarios in this binary classification problem. MATLAB based graphic user interface (GUI) is developed to allow interactive user training for this purpose. The Fig. 6, has this GUI's screen shot. The binary classification ML algorithm is tested with different sizes of data set and its false alarm and target miss rate are tabulated in Table **??**I. The higher training data can make the algorithm more accurate. automatic detection of manmade object detection can be used to alert military team. The Reconnaissance and surveillance aircrafts are enabled with SAR imaging technology. Automatic processing on these images can increase the capability detect small targets within less time. By principle the algorithm does not limit even for ocean applications, however different training data would be required for more accurate results.

The SAR imaging is advantageous in comparison with normal imaging as it can be performed during day time and also night time. In addition as the RF waves can penetrate through clouds the SAR imaging is preferred.

V.

14 Conclusions

The Experiment is performed on a set of 15 SAR Images . Each Image is first segmented into regions via Graph cut Image Segmentation using Radial Basis kernel function. Machine learning algorithm is applied to classify each region to either Natural or Manmade Object. It has been observed that with a training set of 100 the achieved classification accuracy is 67%. With higher training data set the accuracy can be further improved. The proposed method establishes the RBF kernel based machine learning approach for arriving at optimal parameters for kernel function and classification problem. The work is aimed to be continued for studying the utilization of different other kernel for the image processing applications and arriving at optimal parameter selection by machine learning approaches.

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1

Figure 1: 1 .

2

Figure 2: Figure 2 :

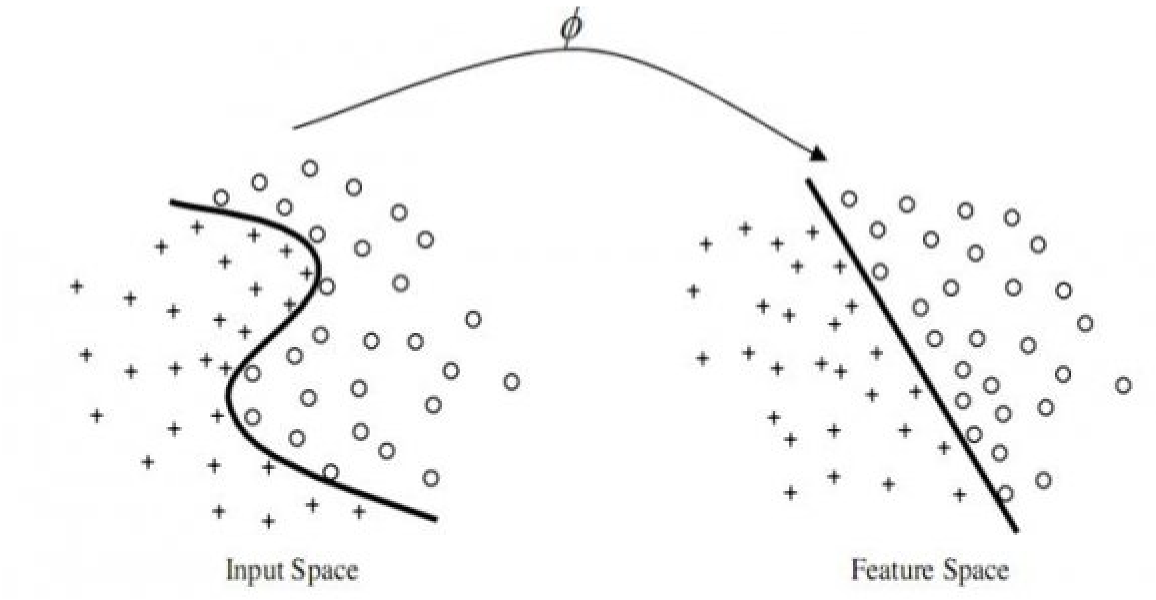

Figure 3: F

3ϕ

Figure 4: Figure 3 :

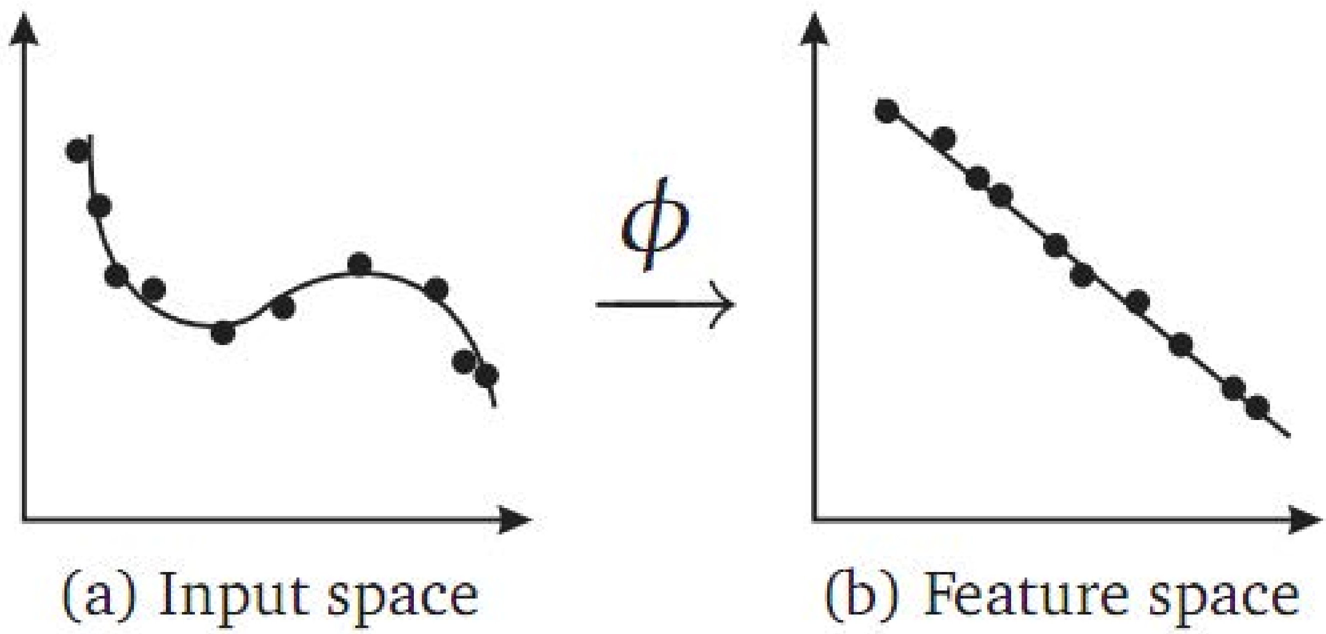

Figure 5:

4 

Figure 6: Figure 4 :

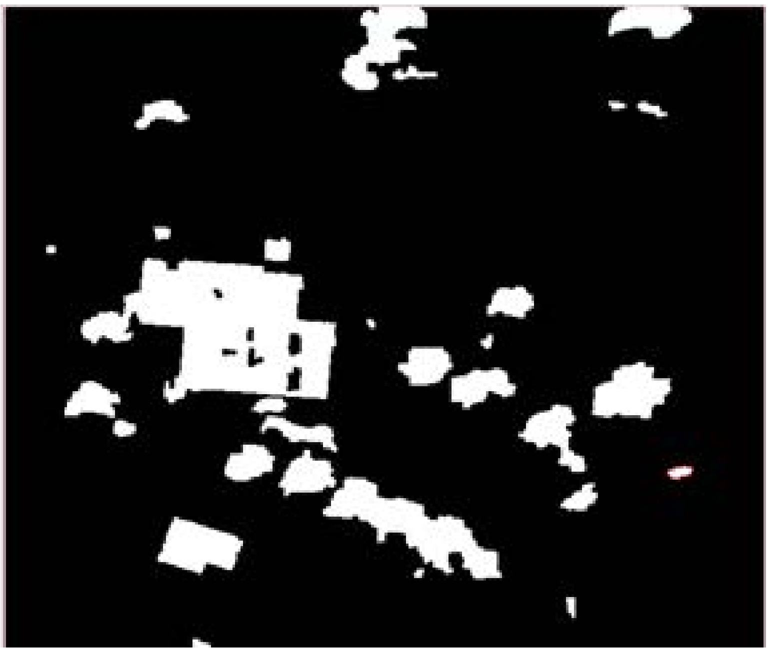

Figure 7:

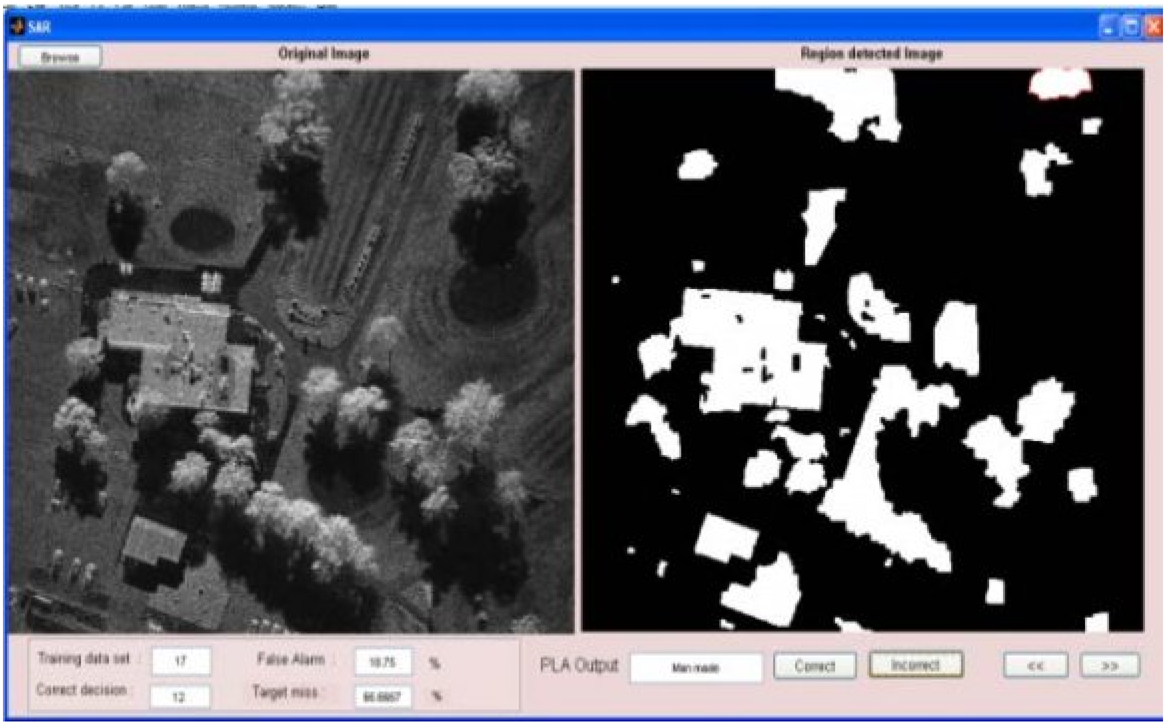

Figure 8: F?

1

Algorithm declared result	Actual scene on SAR image object Manmade	Natural object
Man made object	CORRECT DECISION	FALSE ALARM
Natural object	TARGET MISS	CORRECT DECISION

Figure 9: Table 1 :

2

Sl. No.	Improvement analysis of ML algorithm with larger data set Training data set size	False alarm	Target miss
1	20	18.75%	66.67%
2	50	16.78%	33.33%
3	100	15.73%	22.48%

Figure 10: Table 2 :

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[Salah et al.] ‘A continuous labeling for multiphase graph cut image partitioning’. M B Salah , A Mitiche , I B Ayed . *Advances in Visual Computing*, Lecture Notes in Computer Science G B Lncs) (ed.) (Ed)

[Unnikrishnan et al. (2005)] ‘A measure for objective evaluation of image segmentation algorithms’. R Unnikrishnan , C Pantofaru , M Hebert . *Mathematical Problems in Image Processing: Partial Differential Equations and the Calculus of Variations*, (New York) Jun. 2005. 2006. Springer-Verlag. 3. (Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit.)

[Doerry and Dubbert] *A portfolio of fine resolution Ka-band SAR images: part I*, A W Doerry , D F Dubbert . `http://www.sandia.gov/RADAR-/images/ka_band_portfolio.pdf`

[Cremers et al. ()] ‘A review of statistical approches to level set segmentation: Integrating color, texture,motion andshape’. D Cremers , M Rousson , R Deriche . *Int. J. Comput. Vis* 2007. 72 (2) p. .

[Destrempes et al. (2005)] ‘A stochastic method for Bayesian estimation of hidden Markov random field models with application to a color model’. F Destrempes , M Mignotte , J.-F Angers . *IEEE Trans. Image Process* Aug. 2005. 14 (8) p. .

[Chan and Vese (2001)] ‘Active contours without edges’. T F Chan , L A Vese . *IEEE Trans. Image Process* Feb. 2001. 10 (2) p. .

[Vese and Chan ()] ‘Amultiphase level set framework for image segmentation using the Mumford ans Shahmodel’. L A Vese , T F Chan . *Int. J. Comput. Vis* 2002. 50 (3) p. .

[Leclerc ()] ‘Constructing simple stable descriptions for image par-titioning’. Y G Leclerc . *Int. J. Comput. Vis* 1989. 3 (1) p. .

[Felzenszwalb and Huttenlocher ()] ‘Efficient graph-based image segmentation’. P Felzenszwalb , D Huttenlocher . *Int. J. Comput. Vis* 2004. 59 (2) p. .

[Boykov et al. (2001)] ‘Fast approximate energy minimization via graph cuts’. Y Boykov , O Veksler , R Zabih . *IEEE Trans. Pattern Anal. Mach. Intell* Nov. 2001. 23 (11) p. .

[Caselles et al. ()] ‘Geodesic active contours’. V Caselles , R Kimmel , G Sapiro . *Proc. Int. Conf. Comput. Vis*, (Int. Conf. Comput. Vis) 1995. p. .

[Vazquez et al. (2004)] ‘Image segmentation as regularized clustering: A fully global curve evolution method’. C Vazquez , A Mitiche , I B Ayed . *Proc.IEEE Int. Conf. Image Processing*, (.IEEE Int. Conf. Image essing) Oct. 2004. p. .

[Boykov and Jolly ()] ‘Interactive graph cuts for optimal boundary and region segmentation of objects in N-D images’. Y Boykov , M.-P Jolly . *Proc.IEEE Int. Conf. Comput. Vis*, (.IEEE Int. Conf. Comput. Vis) 2001. p. .

[Blake et al. ()] ‘Intertive image segmentation using an adaptive GMMRF model’. A Blake , C Rother , M Brown , P Perez , P Torr . *Proc. Eur. Conf. Comput. Vis*, (Eur. Conf. Comput. Vis) 2004. p. .

[Aubert and Kornprobst ()] *Mathematical Problems in Image Processing: Partial Differential Equations and the Calculus of Variations*, G Aubert , P Kornprobst . 2006. New York: Springer-Verlag.

[Morel and Solimini ()] J M Morel , S Solimini . *Variational Methods in Image Segmentation*, (Cambridge, MA) 1995. Birkhauser.

[Ben ()] ‘Multiregion Image Segmentation by Parametric Kernel Graph cuts’. Mohammed Ben , Salah . *IEEE Trans on Image Processing* 2011. 20 (2) .

[Ayed et al. (2005)] ‘Multiregion level-set parti-tioning of synthetic aperture radar images’. I B Ayed , A Mitiche , Z Belhadj . *IEEE Trans. Pattern Anal.Mach. Intell* May 2005. 27 (5) p. .

[Shi and Malik (2000)] ‘Normalized cuts and image segmentation’. J Shi , J Malik . *IEEE Trans. Pattern Anal. Mach. Intell* Aug. 2000. 22 (8) p. .

[Shi and Malik (2000)] ‘Normalized cuts and image segmentation’. J Shi , J Malik . *IEEE Trans. Pattern Anal. Mach. Intell* Aug.2000. 22 (8) p. .

[Mumford and Shah ()] ‘Optimal approximation by piecewisesmooth functions and associated variational problems’. D Mumford , J Shah . *Comm. Pure Appl. Math* 1989. 42 p. .

[Zhu and Yuille (1996)] ‘Region competetion: Unifying snakes, region growing, and bayes/MDL for multiband image segmentation’. S C Zhu , A Yuille . *IEEE Trans. Pattern Anal. Mach. Intell* Jun. 1996. 18 (6) p. .

[Vu and Manjunath ()] ‘Shape prior segmentation of multiple objects with graph cuts’. N Vu , B S Manjunath . *Proc. IEEE Int. Conf. Comput. Vis.Pattern Recognit*, (IEEE Int. Conf. Comput. Vis.Pattern Recognit) 2008. p. .

[Jain et al. (2000)] 'Statistical pattern recognition: A review'. A Jain , P Duin , J Mao . *IEEE Trans. Pattern Anal. Mach. Intell* Jan.2000. 22 (1) p. .

[Yang et al. ()] 'Unsupervised segmentation of natural images via lossy data compression'. Y Yang , J Allen , Y Wright , S S Ma , Sastry . *Comput. Vis. Image Understand* 2008. 110 (2) p. .