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Modulated Intensity Gradient and Texture Gradient Based Image Segmentation

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Abstract – Image segmentation is currently a prominent topic for both military and commercial researchers. This paper concentrates on the image segmentation based on the combination of modulated intensity gradient and texture gradient. Image segmentation is an integral part of image analysis. In image processing different processes are done on images to enhance it at different parameters. These processes are not directly applied on images but before that it needs to be segmented or divided in smaller parts called pixels or small blocks of pixels. So segmentation becomes an integral and basic part in image analysis and error at this stage can influence other processing techniques. The performance of this method is compared with the available techniques. The proposed system improves the Mean Square Error (MSE), Maximum Error (MAXERR) and Peak Signal to Noise Ratio (PSNR).

Index Terms – Image, Dual Tree Discrete Wavelet Transform (DT-DWT), Wavelet Transform (WT), Mean Square Error (MSE), Maximum Error (MAXERR), Peak Signal to Noise Ratio (PSNR).

1. INTRODUCTION

Dealing with information extracted from a natural image, a medical scan, satellite data or a frame in a video sequence is the purpose of image analysis. In the real world, the stimulus that is received by the retina is perceived as whole and complete information. Between the electromagnetic reception and the perception, physiological and neurological processes construct the final perception and analysis of the image. In fact vision is composed of many interacting components including analysis of color, texture and shape, the whole conducted by prior knowledge of the human brain. Computer vision aims at getting the same result as human perception. The computer interface receives the image as a matrix of pixels and several levels of processes are involved to get, when it is possible, the same result as human analysis.

The collection of processes involved in the visual perception are usually hierarchically classified as belonging to either low level vision or high level vision. High level vision consists of the interpretation of the image following some rule or prior knowledge. In low level vision, image processing is performed to extract some visible physical properties in the image such as shape and boundaries or to improve the quality of the image. In this thesis we will be dealing with image processing and more precisely with the image segmentation task. The objective of segmentation methods is to determine a partition of an image into a finite number of semantically important regions such as anatomical or functional structures in medical images or objects in natural images. The segmentation task has been studied for several decades; however it is still a challenging task. This task is essential in many applications including face detection in video sequences, changes detection in satellite images, anatomical or functional object extraction in medical images or object extraction in natural images.

An image is essentially a 2-D signal processed by the human visual system. The signals representing images are usually in analog form. However, for processing, storage and transmission by computer applications, they are converted from analog to digital form. A digital image is basically a 2-Dimensional array of pixels. The image is defined in a continuous space and the segmentation problem is expressed through a functional or energy optimization. Depending on the object to be segmented, this energy definition can be difficult; in particular for objects with ambiguous borders or objects with textures. For the latter, the difficulty lies already in the definition of the term texture. The human eye can easily recognize a texture, but it is quite difficult to find words to define it, even more in mathematical terms. This is why we are first interested in the extraction of texture features that is to say, finding one representation that can discriminate a textured region from another. The usefulness of the segmentation is ultimately dependent on the features used for the annotation of data and its efficiency is dependent on the invariance and robust properties of these features. For texture based features an important form of invariance is rotational invariance. This work describes effective and novel texture characterization and rotationally invariant texture characterization techniques. However, watershed segmentation is often not effective for textured image regions that are perceptually homogeneous. In order to properly segment such regions the concept of the “texture gradient” is implemented.

When texture images are considered there is no formal mathematical definition for texture images. It is considered to be complex visual patterns, composed of spatially organized entities that have characteristics like brightness, color, shape, size. Simply it is considered to be a regular repetition of an element or pattern on a surface. Data for texture image can be taken from natural texture, material texture etc [9]. Some of the pictorial representation of natural and material texture is shown in figure 1.

(a) Material Texture.

(b) Natural Texture

Figure 1: Textures.

Image segmentation is a process of partitioning digital image into multiple segments that is set of pixels also known as superpixels. In image segmentation the goal is to simplify or change representation of image into something that is more meaningful and easier to analyze [3]. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics [8]. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic [9].

Texture-based image segmentation is a fundamental task for computer vision and is especially challenging for medical image processing due to following characteristics: 1) complexity of medical images; 2) absence of models of the anatomy that fully capture the possible deformations in each structure; 3) individual differences between patients and image sources; 4) differences in image quality from different sites, etc..

2. SEGMENTATION

Image segmentation refers to the process of partitioning a digital image into N number of parts. The images are segmented on the basis of set of pixels or pixels in a region that are similar on the basis of some homogeneity criteria such as color, intensity or texture, which helps to locate and identify objects or boundaries in an image [2].

In terms of mathematical formulae, Image segmentation divides a digital image f(x, y) into continuous, disconnect and nonempty subsets, from these subsets higher level information can be easily extracted. Practical applications of image segmentation include object identification and recognition, facial recognition, medical image processing, criminal investigation, airport security system, satellite images, quality assurance in factories, etc [3][4]. Due to the importance of the image segmentation, large number of algorithms has been proposed but the selection of the algorithm purely depends upon the image type and the nature of the problem [2].

In recent years, a lot of research is done in the field of image segmentation process. There are currently thousands of algorithms, each doing the segmentation process slightly different from another, but still there is no particular algorithm that is applicable for all types of digital image, fulfilling every objective. Thus, algorithm developed for a group of images may not always apply to images of another class [2] [5].

Currently image segmentation approach, based on two properties of an image, is divided into two categories:

- *Discontinuities based*

In this category, subdivisions of images are carried out on the basis of abrupt changes in the intensity of grey levels of an image. Our focus is primarily based on identification of isolated points, lines and edges. This includes image segmentation algorithms like edge detection.

- *Similarities based*

In this category, subdivision of images are carried out on the basis of similarities in intensity or grey levels of an image. Our focus here is on identification of similar points, lines and edges. This includes image segmentation algorithms like thresholding, region growing, region splitting and merging.

3. DUAL TREE DISCRETE WAVELET TRANSFORM (DT-DWT)

The classical discrete wavelet transform (DWT) provides a means of implementing a multiscale analysis, based on a critically sampled filter bank with perfect reconstruction. However, questions arise regarding the good qualities or properties of the wavelets and the results obtained using these tools, the standard DWT suffers from the following problems described as below:

1. *Shift sensitivity:* It has been observed that DWT is seriously disadvantaged by the shift sensitivity that arises from down samples in the DWT implementation.

2. *Poor directionality:* An m-dimension transform (m>1) suffers poor directionality when the transform coefficients reveal only a few feature in the spatial domain.

3. *Absence of phase information:* Filtering the image with DWT increases its size and adds phase distortions; human visual system is sensitive to phase distortion. Such DWT implementations cannot provide the local phase information.

In other applications, and for certain types of images, it is necessary to think of other, more complex wavelets, which gives a good way, because the complex wavelets filters which can be made to suppress negative frequency components. The complex wavelet transform has improved shift-invariance and directional selectivity. This analyzes the signal by two different DWT trees, with filters chosen so that at the end, the signal returns with the approximate decomposition by an analytical wavelet.

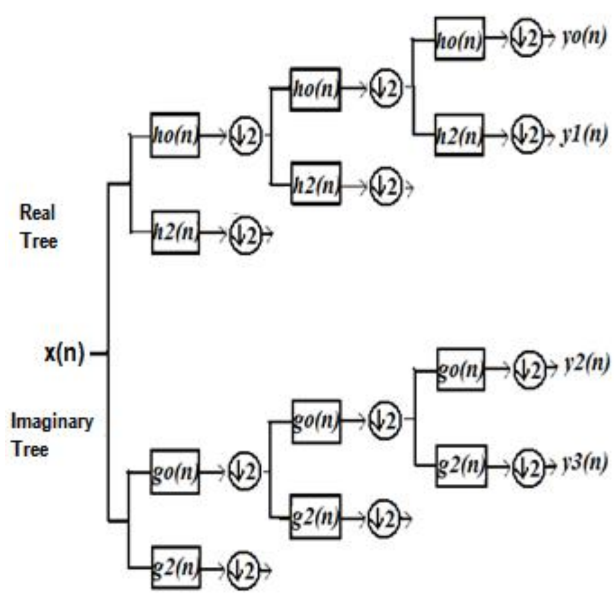

Figure 2: Implementation of Dual-Tree Discrete Wavelet Transform.

The dual-tree structure has an extension of conjugate filtering in 2-D case. Because of the existence of two trees the second noise coefficients moments from such decomposition can be precisely characterized. The DT-DWT ensures filtering of the results without distortion and with a good ability for the localization function and the perfect reconstruction of signal. Moreover, the dual-tree DWT can be used to implement 2D wavelet transforms where each wavelet is oriented, which is especially useful for image processing.

4. TEXTURE BASED SEGMENTATION

The term texture is difficult to define, but it represents aspects of the surface pattern, such as coarseness, directionality, brightness, colour, regularity, and so forth. Texture is a phenomenon that is widespread, easy to recognise and hard to define. Texture features can be used to segment. In remote sensing it is quite usual to segment scenes into different types of land, such as forest, vineyards, urban, streets, lakes.

Texture plays an important role in many machine vision tasks such as surface inspection, scene classification, and surface orientation and shape determination. For example, surface texture features are used in the inspection of semiconductor wafers, gray-level distribution features of homogeneous textured regions are used in the classification of aerial imagery, and variations in texture patterns due to perspective projection are used to determine three dimensional shapes of objects.

Texture is characterized by the spatial distribution of gray levels in a neighborhood. Thus, texture cannot be defined for a point. The resolution at which an image is observed determines the scale at which the texture is perceived. For example, in observing an image of a tiled floor from a large distance we observe the texture formed by the placement of tiles, but the patterns within the tiles are not perceived. When the same scene is observed from a closer distance, so that only a few tiles are within the field of view, we begin to perceive the texture formed by the placement of detailed patterns composing each tile. For our purposes, we can define texture as repeating patterns of local variations in image intensity which is too fine to be distinguished as separate objects at the observed resolution. Thus, a connected set of pixels satisfying a given gray-level property which occurs repeatedly in an image region constitutes a textured region. A simple example is a repeated pattern of dots on a white background. Text printed on white paper such as this page also constitutes texture. Here, each gray-level primitive is formed by the connected set of pixels representing each character. The process of placing the characters on lines and placing lines in turn as elements of the page results in an ordered texture. There are three primary issues in texture analysis: texture classification, texture segmentation, and shape recovery from texture.

In texture classification, the problem is identifying the given textured region from a given set of texture classes. For example, a particular region in an aerial image may belong to agricultural land, forest region, or an urban area. Each of these regions has unique texture characteristics. The texture analysis algorithms extract distinguishing features from each region to facilitate classification of such patterns. Implicit in this is the assumption that the boundaries between regions have already been determined. Statistical methods are extensively used in texture classification. Properties such as gray-level co-occurrence, contrast, entropy, and homogeneity are computed from image gray levels to facilitate classification. The statistical methods are particularly useful when the texture primitives are small, resulting in microtextures. On the other hand, when the size of the texture primitive is large, it becomes necessary to first determine the shape and properties of the basic primitive and then determine the rules which govern the placement of these primitives, forming macrotextures.

5. MODULATED INTENSITY GRADIENT BASED SEGMENTATION

Gradient is the first derivative for image f(x, y), when there is an abrupt change in the intensity near edge. Modulated intensity gradient based method involves convolving gradient operators with the image. High value of gradient magnitude can be points with abrupt change between intensities of the two regions. These points are called edge pixels and can be linked together to form closed boundaries. Normally sobel operator, canny operator, Laplace operator, Laplacian of Gaussian (LOG) operator etc is used as operator in modulated intensity gradient based method. Usually canny operator is used but it takes more time as compared to sobel operator.

In practice edge detection algorithms require a balance between detecting edges accurately and reducing the level of noise. If the level of accuracy is too high, noise will create detection of numerous additional and fake edges. On the other hand, if we try to reduce the level of noise too greatly, we might reduce the accuracy of the edges and many of the useful edges might not be detected.

6. PARAMETERS UNDER CONSIDERATION

Image Quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem. There are several techniques and metrics that can be measured objectively and automatically evaluated by a computer program. Therefore, they can be classified as Full Reference Methods (FR) and No-Reference Methods (NR). In FR image quality assessment methods, the quality of a test image is evaluated by comparing it with a reference image that is assumed to have perfect quality. NR metrics try to assess the quality of an image without any reference to the original one.

The image quality indices try to figure out the some or the combination of the various factors that determine the quality of the image. Some of the parameters analyzed in this dissertation work are

1. Mean Square Error (MSE):

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij} - B_{ij}\right)^2$$

Where m is the height of the Image implying the number or pixel rows.

n is the width of the image, implying the number of pixel columns.

A_{ij} being the pixel density values of the perfect image.

B_{ij} being the pixel density values of the segmented image.

Mean square error is one of the most commonly used error projection method where, the error value is the value difference between the actual data and the resultant data. The mean of the square of this error provides the error or the actual difference between the expected/ideal results to the obtained or calculated result.

Here, the calculation is performed at pixel level. A total of m*n pixels are to be considered. A_{ij} will be the pixel density value of the perfect image and B_{ij} being that of the segmented image. The difference between the pixel density of the perfect image and the segmented image is squared and the mean of the same is the considered error. MSE value will be 0 if both the images are identical.

2. Peak signal-to-noise ratio (PSNR)

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is most easily defined via the mean squared error (*MSE*).

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}\left(MAX_I\right) - 10 \cdot \log_{10}\left(MSE\right) \end{aligned}$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255.

3. MAXERR

MAXERR is the maximum absolute squared deviation of the data, from the approximation.

7. STEPS INVOLVED IN THE PROPOSED ALGORITHM

Steps involved in the proposed system are:

1. The input coloured image is read.
2. The coloured input image is converted to grey image. The grey image is doubled.
3. Firstly, segmentation of image is done using modulated intensity gradient.
4. The segmented output MG is generated.
5. PSNR, MSE and MAXERR are calculated for MG.
6. Secondly, the grey image is segmented using texture gradient.
7. The segmented output TG is generated.
8. PSNR, MSE and MAXERR are calculated for TG.
9. The outputs TG and MG are summed to get the final output of PS.
10. PSNR, MSE and MAXERR are calculated for PS.
11. The PSNR, MSE and MAXERR for final output of PS are compared to PSNR, MSE and MAXERR of TG and MG both.

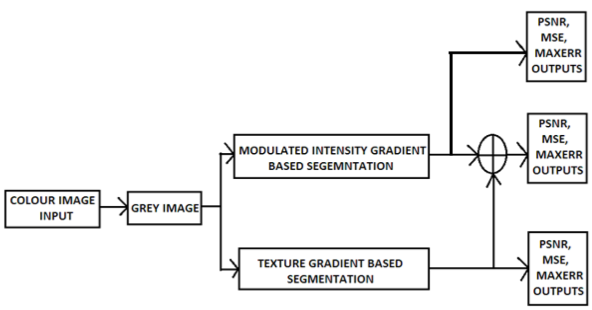

Figure 3: Simulation flow diagram.

8. SIMULATION RESULTS

The proposed system simulation outputs are as under.

Figure 4: Original image.

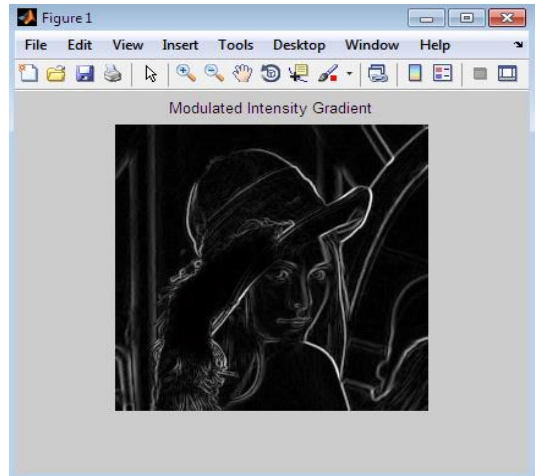

Figure 5: Segmented Image output using modulated intensity gradient.

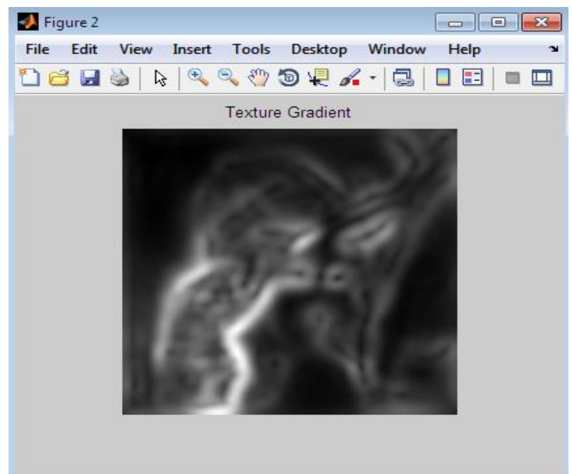

Figure 6: Segmented Image output using texture gradient.

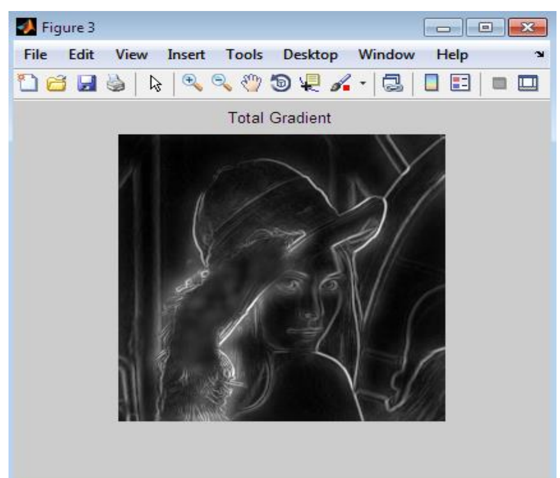

Figure 7: Final Segmented Image output.

The figure 4 shows the original image which is to be segmented. Figure 5 and 6 shows the segmented image outputs by using modulated intensity gradient and texture gradient. Figure 7 shows final output obtained by summing the two output images. From image outputs it can be seen that the final output image is better than the other two output images.

Table 1: Various parameters values obtained.

S.NO	METHODS	PSNR	MSE	MAXERR
1	Modulated intensity gradient based segmentation	5.7806	1.7180e+004	233.7281
2	Texture gradient based segmentation	5.8182	1.7032e+004	234.4981
3	Proposed system	5.8460	1.6923e+004	232.7530

Table 1 shows values of PSNR, MSE and MAXERR obtained by image segmentation using modulated intensity gradient, texture gradient and proposed system. From the table it can be seen that the results with proposed system are better than that with other two traditional systems.

9. CONCLUSION

The objective of this dissertation work is to develop an efficient image segmentation system so that better image can be obtained on reconstruction. In the proposed system two algorithms modulated intensity gradient and texture gradient are used for image segmentation.

Results are derived for modulated intensity gradient based system and texture gradient system and for the proposed system. The parameters of comparison are PSNR, MSE and MAXERR. The results show that the PSNR, MSE and MAXERR values for proposed system are better than the existing system and hence it can be concluded that the proposed system performance has enhanced.

REFERENCES

[1]. Sajan Kor, Pramod Kumar Sethy "*Interactive Image Segmentation using Color and TextureFeatures"*, International Journal of Computer Applications (0975 – 8887) Volume 136 – No.9, February 2016.

[2]. Sun Yongqian and Xi Liang , *"A New Parallel Segmentation Algorithm for Medical Image"* , International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 8, No. 2 (2015), pp. 139-146.

[3]. Priyanka Shivhare, Vinay Gupta,"*Review of Image Segmentation Techniques Including Pre & Post Processing Operations*", International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-4 Issue-3, February 2015.

[4]. Muhammad Waseem Khan, "*A Survey: Image Segmentation Techniques*", International Journal of Future Computer and Communication, Vol. 3, No. 2, April 2014.

[5]. Prabhishek Singh, Ramneet Singh Chadha, "*A Novel Approach to Image Segmentation"*, International Journal of Advanced Research in Computer Science and Software Engineering Volume 3, Issue 4, April 2013.

[6]. *M*. Joseph Prakash, Saka Kezia, I. Santhi Prabha and V. Vijaya Kumar, *"A New Approach for Texture Segmentation Using Gray Level Textons"*, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 6, No. 3, June, 2013.

[7]. P.P.Acharjya1, A. Sinha2, S.Sarkar3, S.Dey4, S.Ghosh, "*A new approach of watershed algorithm using distance transform applied to image segmentation*" International Journal of Innovative Research in Computer and Communication Engineering Vol. 1, Issue 2, April 2013.

[8]. M. Erdt, S. Steger, G. Sakas, "*A New View of Image Segmentation and Registration",* GermanyCopyright © 2012 Journal of Radiation Oncology Informatics ISSN: 1663-618X, J Radiat Oncol Inform 2012;4:1:1-23.

[9]. Anju Bala, "*An Improved Watershed Image Segmentation Technique using MATLAB",* International Journal of Scientific & Engineering Research Volume 3, Issue 6, June-2012 1 ISSN 2229-5518.

[10]. D.Sasirekha, Dr.E.Chandra, *"Enhanced Techniques for PDF Image Segmentation and Text Extraction"*, (IJCSIS) International Journal of Computer Science and Information Security Vol. 10, No. 9, September 2012.

[11]. Ashraf A. Aly1, Safaai Bin Deris2, Nazar Zaki, *"Research review for digital image segmentation techniques",* International Journal of Computer Science & Information Technology (IJCSIT) Vol 3, No 5, Oct 2011.

[12]. D. Maheswari 1, Dr. V.Radha2*,"Enhanced Hybrid Compound Image Compression Algorithm Combining Block and Layer-based Segmentation",* The International Journal of Multimedia & Its Applications (IJMA) Vol.3, No.4, November 2011.

[13]. V. Dey a , Y. Zhang a, M. Zhong **,"***A Review On Image Segmentation Techniques With Remote Sensing Perspective",*ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7A.

[14]. Yi Ma, Senior, Harm Derksen, "*Segmentation of Multivariate Mixed Data via Lossy Data Coding and Compression*", IEEE transactions on pattern analysis and machine intelligence, vol. 29, no. 9, september 2007.

[15]. Jitendra Malik, Serge Belongie, Thomas Leung∗And Jianbo Shi, "*Contour and Texture Analysis for Image Segmentation*", Computer Science Division, University of California at Berkeley, Berkeley, CA 94720-1776, USA Received December 28, 1999; Revised February 23, 2001; Accepted February 23, 2001.

[16]. M. Atonini, M. Barlaud, P. Mathieu, and I. Daubechies, "*Image coding using wavelet transform,"* IEEE Trans.Image Processing, vol. 1, pp. 205–220, Apr. 1992.

[17]. Jha, Sonu Kumar, Purnendu Bannerjee, and Subhadeep Banik. *"Random Walks based Image Segmentation Using Color Space Graphs." Procedia Technology* 10 (2013).

[18]. Bhargava, Neeraj, et al. *"Iterative Region Merging and Object Retrieval Method Using Mean Shift Segmentation and Flood Fill Algorithm."*, Advances in Computing and Communications (ICACC), 2013 Third International Conference on. IEEE, 2013.

[19]. Y. Li, J. Sun, C.-K. Tang, and H.-Y. Shum, *"Lazy snapping," in ACM Siggraph*, 2004, pp. 303–308.

[20]. Ning, Jifeng, et al. *"Interactive image segmentation by maximal similarity based region merging."* Pattern Recognition 43.2 (2010): 445-456.

[21]. Felzenszwalb, Pedro F., and Daniel P. Huttenlocher. *"Efficient graph-based image segmentation."* International Journal of Computer Vision 59.2 (2004): 167-181.

[22]. Boykov, Yuri, and Vladimir Kolmogorov. *"An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision."* Pattern Analysis and Machine Intelligence, IEEE Transactions on 26.9 (2004): 1124-1137.

[23]. Çiğla, Cevahir. *"Efficient graph-based image segmentation via speeded-up turbo pixels."* Image Processing (ICIP), 2010 17th IEEE International Conference on. IEEE, 2010.

[24]. Vezhnevets, Vladimir, and Vadim Konouchine. *"GrowCut: Interactive multi-label ND image segmentation by cellular automata."* proc. of Graphicon. 2005.

[25]. Yuan, Ye, and Chuanjiang He. *"Variational level set methods for image*

[26]. *segmentation based on both L2 and Sobolev gradients."* Nonlinear Analysis: Real World Applications 13.2 (2012): 959-966.
[27]. M. Unser, *"Texture classification and segmentation using wavelet frames,"* IEEE trans. On Image Processing, vol. 4, no. 11, pp.1549–1560, 1995.
[28]. B.Wang and L. Zhang, *"Supervised texture segmentation using wavelet transform",* Proc.of the 2003 International Conference on Neural Networks and Signal Processing, 2003, vol.2,pp. 1078-1082.
[29]. Chang- Tsun Li and Roland Wilson, *"Unsupervised texture segmentation using multiresolution hybrid genetic algorithm,"* in Proc. IEEE International Conference on Image Processing ICIP03 ,2003, pp. 1033–1036.
[30]. T.R. Reed and J. M. H. Du Buf, *"A review of recent texture segmentation, feature extraction techniques",* in CVGIP Image Understanding , 1993, pp. 359– 372.
[31]. A.K. Jain and K. Karu, *"Learning texture discrimination masks",* IEEE trans. of Pattern Analysis and Machine Intelligence, vol.18, no. 2, pp. 195-205, 1996.
[32]. Alp Erturk and Sarp Erturk, *"Unsupervised Segmentation of Hyperspectral Images Using Modified Phase Correlation,"* IEEE geoscience and remote sensing letters, vol. 3, no. 4, october 2006.
[33]. Tamas Sziranyi and Maha Shadaydeh, *"Segmentation of Remote Sensing Images Using Similarity-Measure-Based Fusion-MRF Model",* IEEE geoscience and remote sensing letters, vol. 11, no. 9, september 2014.
[34]. A.K. Qin, David A. Clausi, *"Multivariate Image Segmentation Using Semantic Region Growing With Adaptive Edge Penalty,"* IEEE transactions on image processing, vol. 19, no. 8, august 2010.
[35]. Saiqa Khan, Arun Kulkarni, *"Robust Method for Detection of Copy-Move Forgery in Digital Images,"* IEEE geoscience and remote sensing letters, 2010 IEEE.
[36]. Chaobing Huang, Quan Liu, Xiaopeng Li, *"Color Image Segmentation by Seeded Region Growing and Region Merging,",* 2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery, 978-1-4244-5934-6/10/2010 IEEE.
[37]. Chen Zheng, Leiguang Wang, Rongyuan Chen, and Xiaohui Chen, *"Image Segmentation Using Multiregion-Resolution MRF Model",* IEEE geoscience and remote sensing letters, vol. 10, no. 4, july 2013.
[38]. Zhi-hvi Li, Meng zhang, Haibo Liv, *"A fast algorithm of image segmentation based on markov random field"*, 978-1-4673-4685-6112/ 2012, IEEE.
[39]. Yong Xia and Rongchun Zhao, *"Adaptive Segmentation of Textured Images by Using the Coupled Markov Random Field Model",* IEEE transactions on image processing, vol. 15, no. 11, November 2006.
[40]. H. Narkhede, *"Review of image segmentation techniques,"* Int. J. Sci. Mod. Eng, vol. 1, p. 28, 2013.
[41]. J. F. Khan, S. M. A. Bhuiyan, and R. R. Adhami, *"Image Segmentation and Shape Analysis for Road-Sign Detection,"* IEEE Transactions on Intelligent Transportation Systems, vol. 12, pp. 83-96, 2011.
[42]. S. S. Al-Amri and N. V. Kalyankar, *"Image segmentation by using threshold techniques",* arXiv preprint arXiv:1005.4020, 2010.
[43]. T. Schoenemann, F. Kahl, S. Masnou, and D. Cremers, *"A linear framework for region-based image segmentation and inpainting involving curvature penalization",* International Journal of Computer Vision, vol. 99, pp. 53-68, 2012.
[44]. Z. Ji, Y. Xia, Q. Sun, Q. Chen, D. Xia, and D. D. Feng, *"Fuzzy local Gaussian mixture model for brain MR image segmentation",* IEEE Transactions on Information Technology in Biomedicine, vol. 16, pp. 339-347, 2012.
[45]. H. Zhuang, K.-S. Low, and W.-Y. Yau, *"Multichannel pulsecoupled-neural-network-based color image segmentation for object detection,"* IEEE Transactions on Industrial Electronics, vol. 59, pp. 3299-3308, 2012.
[46]. N. T. N. Anh, J. Cai, J. Zhang, and J. Zheng, *"Constrained active contours for boundary refinement in interactive image segmentation,"* in IEEE International Symposium on Circuits and Systems (ISCAS), 2012 2012, pp. 870-873.
[47]. M. A. Savelonas, E. A. Mylona, and D. Maroulis, *"Unsupervised 2D gel electrophoresis image segmentation based on active contours,"* Pattern Recognition, vol. 45, pp. 720-731, 2012.
[48]. B. Wu and Y. Yang, *"Local-and global-statistics-based active contour model for image segmentation,"* Mathematical Problems in Engineering, vol. 2012, 2012.
[49]. K. S. Tan and N. A. M. Isa, "Color image segmentation using histogram thresholding–Fuzzy C-means hybrid approach," Pattern Recognition, vol. 44, pp. 1-15, 2011.
[50]. H. Cao, H.-W. Deng, and Y.-P. Wang, *"Segmentation of M-FISH images for improved classification of chromosomes with an adaptive Fuzzy C-Means Clustering Algorithm,"* IEEE Transactions on Fuzzy Systems, vol. 20, pp. 1-8, 2012.
[51]. M. Gong, Y. Liang, J. Shi, W. Ma, and J. Ma, *"Fuzzy c-means clustering with local information and kernel metric for image segmentation,"* IEEE Transactions on Image Processing, vol. 22, pp. 573-584, 2013.