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Adaptive SLIC Along with Texture Feature based Segmentation of Urban Area

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Abstract—*In earth observation field, accurate and timely detection of urban area is very crucial for digital mapping, city planning, urban land management, military survey. To detect and record the changes which may occur in forest, desert, agricultural, and urban area is the major responsibility of urban region planners and government agencies. Satellite images and very high resolution images play an important role to resolve this issue. The proposed work comprises three steps. First, adaptive gamma normalization is used to control illumination of the scene. This normalization technique is compatible irrespective of resolution of image. Second, adaptive simple linear iterative clustering (adaptive SLIC) is proposed to form clusters of pixels in [labxy] i.e. 5-Dimensional color image plane space. Finally, gray-level co-occurrence matrix is used to evaluate the texture of image. The results of adaptive SLIC along with texture feature show the better segmentation of urban area from forest or land*

Index Terms*: Adaptive gamma normalization, Adaptive simple linear iterative clustering (Adaptive SLIC), Gray-Level co-occurrence matrix (GLCM).*

1. INTRODUCTION

Now a day, detection of urban area has become vital for many applications [1] such as digital mapping, military scrutiny, change detection, emergency safe landing of UAV fight and land exploration [2]. As a prerequisite of urban monitoring, it can effectively indicate building and man-made objects [2]. For updating the information of geographic system, it is helpful for urban region planners and government agencies [1].

Constantly development of the cities leads to change in land cover [3]. Due to dynamic and heterogeneous environment of urban area, periodically detection at acceptable cost is necessary [4]. However, geometric parameters of buildings are crucial to assess. The process of obtaining qualitative and quantitative information is a difficult task especially when high reliability and accuracy is required [5]. There are so many techniques which had been proposed for automatic detection of urban area from satellite images and very high resolution aerial images [1]. In some applications, these images are not feasible for monitoring, because they cover very large urban area [6]. An efficient solution is required, as the huge number of applications depends upon the accuracy of data [7].

In this paper, a pre-processing stage for the detection of urban area from satellite images is presented. The proposed work comprises main three steps. In first step, adaptive gamma normalization is used to enhance the visual quality of images adaptively. This method has an advantage that, any given image can be utilized for normalization without defining the target. In second step, adaptive SLIC is used to generate super-pixels by grouping the pixels based on some feature similarities such as texture or color. In third step, Gray Level Co-occurrence Matrix is used to evaluate the texture of images.

Fig. 1: Urban area

This feature vector can further be used for automatic detection of urban area. The rest of the paper is structured as: in section 2, related work is described. In section 3, technique for the segmentation of urban area along with texture feature is described. In section 5, experimental results are presented and the conclusion in section 6.

2. RELATED WORK

In recent years, numerous methods for the automatic detection of urban area have been proposed. Some of these deploy pattern recognition techniques and classification. Jwan Al-

Doski et. al. [8] employed support vector machine for the extraction of primary information from satellite images and final land use was monitored using post-classification technique of change detection. Chao Tao et. al. [9] integrated the various features of images through multiple kernel learning and graph cut approach was used to refine boundaries of urban area. Adrien Gressin et. al. [10] used supervised machine learning to detect the heterogeneity of various scenes in very high resolution database and 2-Db land cover database. However, this method required improvement in term of versatility and scalability. Caglar Senaras et. al. [11] performed feature space fusion with two layer mechanism of hierarchical classification for automatic detection of building. Lior Weizman et. al. [12] employed visual words method for the segmentation of urban area. After creating visual dictionary, trained urban words were used to detect urban region from testing images. For automatic detection of urban area, these methods require priori database for the training process.

Some of other types of methods used texture and structure characteristics of satellite images. Chao Tao et. al. [13] used Harris operation to extract number of corner points for initial segmentation of build-up area and then unsupervised clustering i.e. spectrum clustering and the graph cut algorithm were used for final detection of build-up area. F. kressler et. al. [4] used the result of spectral mixture analysis for the detection of changes in urban area from satellite images. Beril Sirmacek et. al. [14] proposed scale invariant feature transform (SIFT) method for automatic detection of buildings and urban area from satellite image. However, SIFT alone was not adequate for the detection. So, graph cut method was proposed to formalize this problem. But their approach was not adequate to detect the closely spaced buildings. Then, they [6] used Gabor filters to extract local feature points and proposed a new technique known as spatial voting and optimal decision making approach for the detection of urban area. Then, they [15] employed four different methods of extraction of local features and boundaries of urban area were detected using estimated PDF. Two fusion methods were used in data and decision level to improve the final results. Hao shi et. al. [2] extracted all the corner points from down sampled images and integrated using weighted gaussian voting matrix technique. Then, guided image filtering was used to combine the extracted results of edge detection and homogeneous region and to extract buildings. However, tested results showed some problems and required more improvement. A. Bekkari et. al. [16] used the combined information of space and spectrum to refine the classification results of support vector machine. Spatial domain information was introduced using graph cuts to further improve SVM algorithm.

3. METHODOLOGY

A. Adaptive gamma normalization

Adverse conditions of environment or illumination may degrade the scene chromatics. While, illumination of the scene is difficult to control, gamma normalization is becoming fascinating solution for the enhancement of intensity and color of an image [17]. Non-linear signal as a resultant is obtained after applying gamma normalization each channel of RGB image. Normalization of each channel is performed separately. In adaptive gamma normalization, numeric description of an image can be used to identify the scene in low illumination and in case of change of illumination [18]. The advantages provided by adaptive gamma normalization are as following;

- This technique is appropriate for real-time application.
- With the use of adjustable variable factors, compression of dynamic range is provided.
- This normalization technique is compatible irrespective of data representation bits and resolution of image.
- Wide dynamic range provides mapping of tone with low illumination and change of illumination [18].

Adaptive gamma normalization is a process in which low intensity of scene can be increased progressively and significant decrement in high intensity of image can be avoided [19]. Correction of color and intensity of an image is obtained by simply using adaptive variable parameter Ɣ. The adaptive gamma normalization can be formalized as follows [20]:-

$$T(l) = l_{max}(l/l_{max})^{\text{Ɣ}}$$

Here, l_{max}= maximum intensity of an input image.

l= intensity of each pixel of an input image which is transformed after performing$T(l)$.

The value of Ɣ greater than 1 is depicted as decoding gamma and the value of Ɣ less than 1 is depicted as encoding gamma [21]. Some changes in the contrast will be exhibited by different images with the use of fixed parameter. To solve this problem, probability density function is calculated for each intensity level of input image and can be formulated as [20]:-

$$PDF(l) = n_l/(MN)$$

Here, n= number of pixels in an image having l intensity.

MN= total pixels of an image.

Cumulative distribution function can be directly calculated from probability density function, as:

$$CDF(l) = \sum_{k=0}^{l} PDF(k)$$

The adaptive gamma parameter is based on cumulative distribution function, given as [20]:-

$$\text{Ɣ} = 1 - CDF(l)$$

Otsu method is used to compute initial threshold value and is utilized as target mean to divide an image into foreground and background pixels according to its gray level.

B. Adaptive SLIC based super-pixel segmentation

This approach generates super-pixels by grouping pixels into significant sub-regions based on their proximity and similarity of color feature, to substitute the rigid pixel grid structure. SLIC is a simple and most robust approach to recognize non-homogeneous and homogeneous regions in colored image. The setting of two parameters is needed to generate significant super-pixels: compactness factor m and the desired number of super-pixels k. This is performed in [labxy] i.e. 5-dimensional space, where [lab] in CIELAB color space is pixel color vector and position of pixel can be represented with x, y co-ordinates. While in CIELAB, maximum distance is limited between two colors and the size of image affects the spatial distance. Without the normalization of spatial distance in 5-dimensional space, Euclidean distance cannot be simply used [22]. Therefore, the size of super-pixel is considered in newly introduced distance, to cluster the pixels in 5-dimensional space.

1. Initialization

Assuming the total number of pixels in an image is N and desired number of super-pixels is k for an image of equal size. Each super-pixel is of N/k size. The center or seed point of each super-pixel would be at each S=√N/k pixel. The influence of noisy pixel and location of center of super-pixel on edge pixel can be avoided by moving the seed point to lowest magnitude of gradient to its 3*3 neighborhood. The gradient of image is formulated as:

$$G(x,y) = \left||I(x+1,y) - I(x-1,y)|\right|^2 + ||I(x,y+1) - I(x,y-1)||^2$$

Where, I(x, y) is color vector of pixel at (x, y) co-ordinate. 2S*2S area around seed point is used to search the pixels which are associated with this seed point.

2. Distance measure

Euclidean distances are intuitively meaningful in CIELAB space for small distances. If spatial distances of pixel exceed this intuitive limit of color distance, outweigh to color similarities of pixel begin (resulting more relative importance of proximity rather than the region boundaries). Therefore, $D_s$distance measure is used in 5-dimensional space instead of Euclidean distance [23]. D_s is formulated as:

$$D_s = d_{lab} + \frac{m}{s} d_{xy}$$

Where,

$$d_{lab} = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}$$

and

$$d_{xy} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$

d_{lab} is distance for pixel color and d_{xy} is distance between pixel i and pixel j in x, y co-ordinate. D_s evaluates distance between cluster center C_k and pixel i. The larger value of m results in more compact super-pixel. Small value of m results in less regular shape and size of super-pixel.

In smooth region, SLIC produces super-pixel of smooth and regular-sized and in textured region, SLIC produces highly irregular super-pixels. This problem is avoided by using zero parameter version of SLIC i.e. adaptive SLIC. Adaptive SLIC adaptively choose the compactness factor for an image. Normalized distance for adaptive SLIC can be formulated as:

$$D = \sqrt{(\frac{d_c}{m_c})^2 + (\frac{d_s}{m_s})^2}$$

After first iteration with constant normalization factor, maximum value of color distance and spatial distance (m_c, m_s) is observed from previous iteration is used in following process for normalization of each cluster.

C. GLCM(Gray Level Co-occurrence Matrix)

Texture of an image can be identified using gray level co – occurrence, by modeling the variation of gray level of an image as two-dimensional array, called gray level of co-occurrence matrix [24]. In computer vision field, recognition of texture of an image plays an important role [25]. Second-order statistics measured by GLCM is used to estimate the properties of an image, which is number of gray human vision. In GLCM matrix, number of gray level of image is equal to number of rows and columns. On the basis of relationship between pixels, texture of an image can be analyzed [26]. The frequencies of occurrence of pair of pixels which are separated by certain distance but having same gray level are recorded in GLCM matrix. P(i, j) in GLCM matrix defines as pair of pixel with gray level i and j occurring at d distance apart from each other, along Ө directional [27]. To find the relationship among an arbitrary point and its neighboring pixel, concern is distance among them and the direction. In proposed work, four directions i.e. 0^0,45^0, $90^0$and 135^0 are taken along distance as one, to find out four statistics, that are contrast, co-relation, energy, and homogeneity. So, there are four different values of each statistics. The mathematical equation to calculate elements in matrix is shown below:

$$P_{ij} = \frac{P(i,j|d,\Theta)}{\sum_{i=1}^{n}\sum_{j=1}^{n} P(i,j|d,\Theta)}$$

Energy is a statistic which is used to represent the existence of similar changes in gray scale image and homogeneity changing [25].

$$ENERGY = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{ij}^2$$

Contrast of an image shows how the matrix values are distributed and represents its clarity of an image, increases with the increase in contrast value [25].

$$CONTRAST = \sum_{i=1}^{n}\sum_{j=1}^{n}(i-j)^2 P_{ij}$$

Homogeneity is used to find the occurrence of local changes in an image.

$$HOMOGENEITY = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{1+(i-j)^2}P_{ij}$$

Correlation is used to find the linear dependence of gray among specified and its neighborhood pixels. Joint probability occurrence is computed for specified pixel pairs [28]:

$$CORRELATION = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(i.j)P_{ij} - \mu_x\mu_y}{\sigma_x\sigma_y}$$

Here,

$$\mu_x = \sum_{i=1}^{n}\sum_{j=1}^{n} i.P_{ij}$$

$$\sigma_x = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}(i-\mu_x)^2 P_{ij}}$$

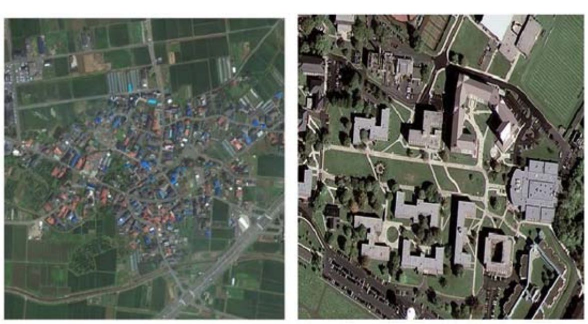
$$\sigma_y = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}(j-\mu_y)^2 P_{ij}}$$

Choice of radius, quantized ray level (G) and radius Θ must be considered while computing GLCM matrix.

4. EXPERIMENTAL RESULTS

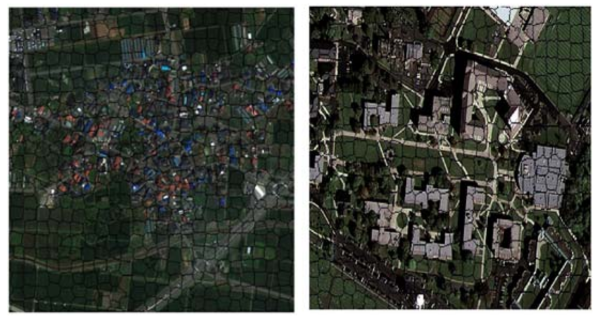
The performance of this method is evaluated on GeoEye-1 and QuickBird satellite images of different cities with spatial resolution of 0.5-meter and 0.61-meter respectively. Numerous scenes such as forest, plains, urban area, mountains, road, and farmlands are covered in these images. All these satellite images have different size.

The results of proposed approach on test images are presented in fig. 2, where the original images are shown in first row. Second row shows the results of adaptive gamma normalization and third row shows the result of adaptive SLIC. The fig 2(c) and 2(d) shows, after applying the adaptive gamma normalization, image has much normalized gamma. The initial threshold value is computed using Otsu's Method.



(a) **(b)**

(c) **(d)**



(e) **(f)**

Fig. 2 (a & b) original images. (c & d) Normalization result. (e & f) Adaptive SLIC result.

After that, an iterative method updates the threshold till no more variation is seen and is utilized as target mean. This mean is then used by gamma normalization equation to compute the gamma normalized image. Adaptive SLIC is used in our work because by default, SLIC requires many control parameters which can be different for each image for correct clustering. Adaptive SLIC only requires a single parameter i.e. the number of super-pixels and the other parameters are computed adaptively thereby giving much accurate result shown in fig 2(e) and 2(f). After all these steps, we have computed GLCM (Gray Level Co-occurrence Matrix) for each super-pixel which resulted into 16 texture features for each super-pixel. In our case, we started with 5000 super-pixel which on general converges to around 4900 super-pixels. Thus applying GLCM texture features for each super-pixel resulted into 4900x16 matrix which is our feature vector computed from a single image.

5. CONCLUSION

We have proposed an adaptive SLIC along with texture feature for better segmentation of urban area from forest or land. Without defining target, any given image can be utilized for normalization with adaptive gamma normalization. The initial threshold value is computed using Otsu's method and selected by an iterative process. Then, the numbers of super-pixels are generated with adaptive SLIC. After all these steps, we have computed GLCM (Gray Level Co-occurrence Matrix) for each super-pixel which resulted into 16 texture features for each super-pixel. This extraction result of texture features serves as pre-processing stage for change detection, city planning and building recognition. In future work, this feature vector will be used to train supervised machine learning technique for accurate detection of urban area.

REFERENCES

[1] C. Zheng, L. Wang, H. Zhao and X. Chen, "Urban area detection from high-spatial resolution remote sensing imagery using Markov random field-based region growing", Journal of applied remote sensing, vol. 8, pp. 083566(1)-083566(14), Aug 2014.

[2] H. Shi, L. Chen, F. Bi, H. Chen, and Y. Yu, "Accurate Urban Area Detection in Remote Sensing Images", IEEE Geosci. Remote Sens. Lett., vol. 12, no. 9, pp. 1948–1952, Sept. 2015.

[3] A. A. Belal and F. S. Moghanm, "Detecting urban growth using remote sensing and GIS techniques in Al Gharbiya governorate", The Egyptian Journal of Remote Sensing and Space Sciences, vol. 14, pp. 73–79, Sept 2011.

[4] F. kressler and K. steinnocher, "Change detection in urban area using satellite images and spectral mixture analysis", International Archives of Photogrammetry and remote sensing", vol. 31, pp. 379-383, 1996.

[5]D. G. Aguilera, E. C. Matellán, D. H. López, and P. R. Gonzálvez, "Automated Urban Analysis Based on LiDAR-Derived Building Models", IEEE Geosci. Remote Sens. Lett., vol. 51, no. 3, pp. 1844–1852, Mar. 2013.

[6] B. Sirmacek and C. Unsalan, "Urban area detection using local feature points and spatial voting," IEEE Geosci. Remote Sens. Lett., vol. 7, no. 1, pp. 146–150, Jan. 2010.

[7] A. Taneja, L. Ballan and M. Pollefeys, "Geometric Change Detection in Urban Environments using Images",IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 6, no. 1, pp. 1-14, Jan. 2007. [8] J. A. Doski, S. B. Mansor, H. Z.M. Shafri, "Support Vector Machine Classification to Detect Land Cover Changes in Halabja City, Iraq", IEEE Business Engineering and Industrial Application Colloquium, pp. 353-358, 2013.

[9] C. Tao, Y. Tan J. Yu and J. Tian, "urban area detection using multiple kernel learning and graph cut", Proceedings of IEEE International Conference on Geoscience and Remote Sensing Symposium, pp. 82-86, 2012.

[10] A. Gressin, N. Vincent, C. Mallet and N. paparoditis, "A unified framework for land-cover database update and enrichment using satellite imagery", Proceedings of IEEE International Conference on Image Processing, pp. 5057-5061, 2014.

[11] C. Senaras, B. Yuksel, M. Ozay, and F. Yarman-Vural, "Automatic building detection with feature space fusion using ensemble learning," Proceedings of IEEE International Conference on Geoscience and Remote Sensing Symposium , 2012, pp. 6713–6716.

[12] L.Weizman and G. Jacob, "Urban-area segmentation using visual words," IEEE Geosci. Remote Sens. Lett., vol. 6, no. 3, pp. 388–392, Jul. 2009.

[13] C. Tao, Y. Tan, Z.-R. Zou, and J. Tian, "Unsupervised detection of built-up areas from multiple high-resolution remote sensing images", IEEE Geosci. Remote Sens. Lett., vol. 10, no. 6, pp. 1300–1304, Nov. 2013.

[14] B. Sirmacek and C. Unsalan, "Urban-area and building detection using SIFT keypoints and graph theory," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 4, pp. 1156–1167, Apr. 2009.

[15] B. Sirmaçek and C. Unsalan, " Urban area detection from remotely sensed images using combination of local features", Proceedings of IEEE International conference on Recent Advances in Space Technologies, pp. 188-192, Jun. 2011.

[16] A. Bekkari, S. Idbraim , D. Mammass and M. E. Yassa, "Exploiting spectral and space information in classification of high resolution urban satellites Images using Haralick features and SVM", Proceedings of IEEE International conference on multimedia computing and systems, Apr. 2011.

[17] N. M. Kwok, D. Wang, X. Jia, S.Y. Chen, G. Fang and Q.P. Ha, "Gray World based Color Correction and Intensity Preservation for Image Enhancement", Proceedings of 4th IEEE International Conference on image and Signal Processing, pp. 994-998, 2011.

[18] Y. M. Jang, J. H. Cho, J. G. Kim, B. C. Kim, S. B. Cho, "Enhanced Tone Mapping of High Dynamic Range to Correspond to Illumination Changes", Proceedings of International Soc Design Conference, pp. 258-289,2014.

[19] A. Aggarwal, R.S. Chauhan and K. Kaur , "An Adaptive Image Enhancement Technique Preserving Brightness Level Using Gamma Correction", Advance in Electronic and Electric Engineering, vol. 3, no. 9, pp. 1097-1108, 2013.

[20] S.C. Huang, F. C. Cheng, and Y. S. Chiu, "Efficient Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution", IEEE Trans. On Image Processing, vol. 22, no. 3, pp. 1032-1041, Mar. 2013.

[21] C. C. O. Chollette, G. SUlong, Uche A. K. Chude-Okonkwo3, Siti z. M. Hashim, "Illumination Normalization for Edge-Based Face Recognition Using the Fusion ofRGB Normalization and Gamma Correction", Proceedings of IEEE International Conference on Signal and Irnage Processing Applications, pp. 412-416, 2013.

[22] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk, " SLIC superpixels", _Ecole Polytechnique F_edrale de Lausanne (EPFL) Technical Report, pp. 1-15, Jun 2010.

[23] D. Chen, S. Shang, and C. Wu, "Shadow-based Building Detection and Segmentation in High-resolution Remote Sensing Image", Journal of Multimedia, vol. 9, no. 1, Jan. 2014.

[24] S. Abbasi and F. TajeriPour, "A Hybrid Approach for Detection of Brain Tumor in MRI Images", Proceedings of 21st Iranian Conference on Biomedical Engineering, pp. 269-274, Nov. 2014.

[25] V. K. Bhad and K. Ramteke, "Content Based Image Retrieval a Comparative Based Analysis for Feature Extraction Approach", Proceedings of International Conference on Advances in Computer Engineering and Applications, pp. 260-266, 2015.

[26] U. Mokhtar, N. E. Bendary, A. E. Hassenian, E. Emary, M. A. Mahmoud, H. Hefny and M. F. Tolba, "SVM-Based Detection of Tomato Leaves Diseases", Springer Advances in Intelligent Systems and Computing, pp. 641-652, 2015.

[27] K. I. Chang, K. W. Bowyer and M. Sivagurunath, "Evaluation of Texture Segmentation Algorithms", Proceedings of IEEE Computer Society Conference on Computer vision and Pattern Recognition, vol. 1, pp. 294-299, Jun. 1999.

[28] M. D. Yang, T. C. Su, N. F. Pan, P. Liu, "Feature Extraction of Sewer Pipe Failure by Wavelet transform and Co-occurrence Matrix", Proceedings of the 2008 International Conference on Wavelet Analysis and Pattern Recognition, pp. 579-584, 2008.