IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-9, Sept. 2018 E-ISSN: 2347-2693

Comparison of Texture Extraction & Segmentation of Complex Images using PCA_GMTD & RP-Live Wire Algorithms

Pradnya A. Maturkar[1*], M.A. Gaikwad[2]

[1]Dept. Electronics Engineering, RGCE, Nagpur, RTM University, Nagpur, India
[2]Dept. Electronics & Telecommunication Engineering, GHRCE, Nagpur, RTM University, Nagpur, India

pm_it@rediffmail.com, Tel.: +91-97666-98985

Available online at: www.ijcseonline.org

Accepted: 24/Sept./2018, Published: 30/Sept./2018

Abstract— In our proposed research work, the application of live-wire algorithm has been proposed to segment complex Aerial insulator images along with RP algorithm to extract the features of images. Firstly, Gray Level Co-occurrence Matrix (GLCM) is employed to extract the texture features of image by the rapid Gray Level Co-occurrence Integrated Algorithm (GLCIA). We have categorised extracted texture feature into two: one with the stronger discriminative ability and other with weaker ability. The weaker discriminative ability has optimized by using PCA & RP. Successfully segmenting the complex low contrast aerial images is one of the main focus of this paper.After optimization by PCA, segmentation is done by Global Minimization with Texture Descriptor (GMTD).After optimization by RP, segmentation is done by Live-wire. To analyze the comparative effect of algorithms on optimization & segmentation, we have used Brodatz dataset. We have observed that Random projection is computationally faster than PCA due to random selection of 'best' basis vector which improves the computational speed of RP. Live wire is use to fast segmentation as well as improves weight parameter. Our results demonstrate a 20% improvement in overall system speed and 10% improvement in segmentation accuracy when compared with traditional algorithms .Another advantage of using this technique is that the process is fully automatic thus can be used for training of machine learning and AI based algorithms.

Keywords—*GLCM,GLCIA,Segmentation,GMTD*

I. INTRODUCTION

Image analysis involves investigation of the image data for a specific application. Normally, the raw data of a set of images is analyzed to gain insight into what is happening with the images and how they can be used to extract desired information. In image processing [1] and pattern recognition, feature extraction is an important step, which is a special form of dimensionality reduction. When the input data is too large to be processed and suspected to be redundant then the data is transformed into a reduced set of feature representations. The process of transforming the input data into a set of features is called feature extraction. Features often contain information relative to colour, shape, texture or context. Texture analysis is a significant challenge however due to the complexity of the textural patterns and the infinity of different lighting conditions that mast be taken into account.

Many different kinds of work have been performed by researchers concerning texture-based feature in various remote sensing applications, such as the classification of sea-ice, the extraction of built-up areas, landform mapping and land-use mapping [4]–[7]. Generally, the overall quality of texture segmentation is determined by both the performance of texture features and that of segmentation approach .For the texture feature extraction, there exist various methods such as GLCM (Gray Level Co-Occurrence Matrix), Gabor and MRF (Markov Random Fields) [4], [8].Comparative studies [8] among these methods demonstrated that GLCM has better performance for distinguishing textures. Walker [10] studied the multi scale property of GLCM. The main drawback of GLCM is its high computation complexity. However, it has been well solved by a rapid computational method of GLCIA (Gray Level Co-occurrence Integrated Algorithm) proposed by Clausi [10].In our proposed research work, GLCM is employed to extract texture features using GLCIA. We roughly cluster these features into two categories: one with stronger discriminative ability and the other with weaker ability. The quantities of the first category account for lower ratio such that the segmentation results are not always satisfactory although they have stronger discriminative ability. In contrast, the second category also contains valuable information concerning the low-contrast regions despite of their weaker discriminative ability. In order to obtain stable and accurate segmentation, RP is employed in a new way to optimize the texture features.

In random projection (RP) [3], the original high-dimensional data is projected onto a lower-dimensional subspace using a random matrix whose columns have unit lengths. RP has been found to be a computationally efficient, yet sufficiently accurate method for dimensionality reduction of high-dimensional data sets.

Random projection (RP) [12], [13], [15] refers to the technique of projecting a set of points from a high dimensional space to a randomly chosen low-dimensional subspace. The technique has been used in combinatorial optimization[44], information retrieval, face recognition [23], and machine learning [14], [16]. The information preserving and dimensionality reduction power of RP is firmly evidenced in the emerging theory of compressed sensing (CS) [17], [18], [19], which states that, for sparse and compressible signals, a small number of non-adaptive linear measurements in the form of random projections can capture most of the salient information in the signal and allow for perfect reconstruction of the signal. Moreover, RPs has also played a central role in providing feasible solutions to the well-known Johnson-Lindenstrauss (JL) lemma [13].

As for the segmentation [27],[31],[32],[38],[40],[43] approach, live- wire have been gaining great success and increasing interest. A review of major live-wire can be found in Jian rule and et al. [28] projected associate unattended multi-band approach for scale parameter choice within the multi-scale image segmentation method that uses spectral angle to live the spectral homogeneity of segments. With the increasing scale parameter, spectral homogeneity of segments decreases till they match the objects within the world. The index of spectral homogeneity has been accustomed verify multiple acceptable scale parameters. The performance of the projected methodology was compared to a single-band based mostly methodology through qualitative visual interpretation and quantitative discrepancy measures. Each strategy is applied for segmenting 2 images: a fast Bird scene of associate populated area inside Beijing, China and a Woldview-2 scene of a suburb in Kashiwa, Japan. The projected multi-band based segmentation scale parameter choice methodology outperforms the single band based methodology with the higher recognition for numerous land cov.er objects in several urban landscapes. Jing Liu, Peijun Li and et al. [29] projected a unique image segmentation methodology for VHR multispectral pictures mistreatment combined spectral and morphological data. The strategy may be summarized as follows. First, a morphological spinoff profile has been calculated from an inventive multispectral image and combined with the spectral bands to quantify spectral-morphological characteristics of a pel, that are thought of as a criterion of homogeneity of neighboring pixels. Image segmentation was conducted employing a seeded region-growing procedure, that has been supported the seed points mechanically generated from the gradient image and dynamically intercalary and therefore the similarity between a seed pel and its neighboring pixels in terms of spectral morphological characteristics. The obtained segmentation result was more refined by a section merging procedure to get a final segmentation result. The projected methodology has been evaluated mistreatment 3 VHR pictures of urban and residential district areas and compared with 2 existing segmentation strategies, in terms of visual examination, quantitative analysis and indirect analysis. Experimental results demonstrate that the joint use of spectral and morphological data outperformed the employment of morphological data alone. Moreover, the projected image segmentation methodology performed higher than existing strategies. The projected image segmentation methodology was well applicable to the segmentation of VHR representational process over urban and residential district areas. Zhijian Huang and et al. [30] has projected the novel feature for remote sensing image analysis, referred to as multi-scale relative prominence (MsRS) feature. It had been made by modeling the method of feature price dynamic with scales. Firstly, the multi-scale observation values at every web site are obtained by convolved with algorithmic Gaussian filters for potency. Secondly, the multi-scale observation prices are compared with the initial value to get the relative prominence. Lastly, the relative prominence between multi-scales are engraft into one feature referred to as the MsRS. the dimensions in MsRS has express spatial which means that was convenient to settle on acceptable scale for specified object. Within the MsRS map, the inner of every object become additional consistent, whereas the distinction between object and background has been enlarged. The MsRS may be used as pre-processing step of the many applications, like segmentation. 2 state-of-art segmentations (the mean shift and therefore the applied mathematics region merging) are taken into experiments and therefore the results proven that it brings improvement clearly. Zhongwu Wang and et al. [34] introduced a brand new automatic Region-based Image Segmentation algorithmic rule supported k-means agglomeration (RISA), specifically designed for remote sensing applications [26],[35],[36]. The algorithmic rule includes 5 steps: k-means agglomeration, phase low-level formatting, seed generation, region growing, and region merging. RISA was evaluated employing a case study specializing in land-cover classification for 2 sites: associate agricultural space within the Republic of African nation and a territorial dominion in city, CA. High spatial resolution SPOT five and fast Bird satellite representational process were utilized in the case study. RISA generated extremely homogenous regions supported visual examination. The land-cover classification mistreatment the RISA-derived image segments resulted in higher accuracy than the classifications mistreatment the image segments derived from the Definiens package (eCognition) and original image pixels together with a minimum-distance classifier. Quantitative segmentation quality assessment mistreatment 2 object metrics showed RISA-derived segments with success delineate the reference objects. Xueliang Zhang and et al. [37] projected a Boundary-Constrained Multi-Scale Segmentation (BCMS) methodology. Firstly, adjacent pixels are aggregate to get initial segmentation consistent with the native best region growing strategy. Then, the Region contiguity Graph (RAG) was designed supported initial segmentation. Finally, the native mutual best region merging strategy has been applied on RAG to provide multi-scale segmentation results. Throughout the region merging method, a Step-Wise Scale Parameter (SWSP) strategy has been projected to provide boundary-constrained multi-scale segmentation results. Moreover, so as to enhance the accuracy of object boundaries, the property of edge strength was introduced as a merging criterion. a group of high spatial resolution remote sensing pictures was utilized in the experiment, e.g., Quick Bird, Worldview, and aerial image, to judge the effectiveness of the projected methodology. The segmentation results of BCMS were compared with those of the industrial image analysis package eCognition. The experiment shows that BCMS will manufacture nested multi-scale segmentations with correct and swish boundaries that prove the strength of the projected methodology. Xueliang Zhang and et al. [39] projected a hybrid region merging (HRM) methodology to phase high resolution remote sensing pictures. HRM integrates the benefits of global-oriented and local-oriented region merging methods into a unified framework. The globally most-similar try of regions was accustomed verify the place to begin of a growing region, that provides a sublime thanks to avoid the matter of place to begin assignment and to reinforce the optimization ability for local-oriented region merging. Throughout the region growing procedure, the merging iterations are strained inside the native locality, so the segmentation was accelerated and may mirror the native context, as compared with the global-oriented methodology. a group of high-resolution remote sensing pictures has been accustomed check the effectiveness of the HRM methodology, and 3 region based remote sensing image segmentation strategies were adopted for comparison, together with the hierarchical stepwise optimization (HSWO) methodology, the local-mutual best region merging (LMM) methodology, and therefore the multi resolution segmentation (MRS) methodology embedded in eCognition Developer package. Each the supervised analysis and visual assessment show that HRM performs higher than HSWO and LMM by combining each their blessings. The segmentation results of HRM and MRS were visually comparable, however HRM will describe objects as single regions higher than MRS, and therefore the supervised and unattended analysis results more prove the prevalence of HRM. Jianyu bird genus and et al. [41] projected a brand new approach to multi scale segmentation of satellite multispectral representational process mistreatment edge data. The cagey edge detector was applied to perform multispectral edge detection. The detected edge options were then used in a very multi scale segmentation loop, and therefore the merge procedure for adjacent image objects has been controlled by a disconnectedness criterion that mixes edge data with segmentation scale. The importance of the sting was measured by adjacent partitioned off regions to perform edge assessment. The current methodology has supported a half-partition structure that was composed of 3 steps: single edge detection, separated pel grouping, and vital feature calculation. The spectral distance of the half partitions separated by the sting was calculated, compared, and integrated into the sting data. The results show that the projected approach works well on satellite [33] multispectral pictures of a coastal space.

II. FEATURE EXTRACTION & SEGMENTATION OF PROPOSED WORK

Texture feature of complex images has extracted using GLCIA. Extracted feature has been clustered into two categories by k-mean. After clustering, texture features with weaker discrimination is optimized by PCA and then by RP [25] which we proposed here. Segmentation has been done by GMTD and then by Live-wire which we proposed here. Compare the result PCA_GMTD [2] and proposed RP_live-wire using Brodatz dataset.

A. Proposed Random projection for feature selection

The weak feature set consists of features which are not variant enough in order to describe the different textures of the input image, and thus must be modified in order to be selected. Random projections and random subspace methods are very simple and computationally efficient techniques to reduce dimensionality for learning from high dimensional data. Since high dimensional data tends to be prevalent in many domains. Random projections (RP)[3],[15],[16],[17]are motivated by their proven ability to preserve inter-point distances. By contrary, the random selection of features (RF) appears to be a heuristic, which nevertheless exhibits good performance in previous studies. We find that RP[12],[13],[14],[24],[25] tends to perform better than RF in terms of the classification accuracy in small sample settings , although RF is surprisingly good as well in many cases. Random Projections [21],[22],[23] is a very simple yet powerful technique for dimensionality reduction. In this method the data is projected on to a random subspace, which preserves the approximate Euclidean distances between all pairs of points after the projection.

The Johnson Lindenstrauss lemma (JLL) guarantees that for a set of N points in p dimensions there is a linear transformation to a q dimensional random subspace that preserves the Euclidean distances between any two data points up to a factor of $1+e$ if the number of projected dimensions $q > (\log \frac{n}{e^2})$ where e is a small constant such that $0 < e < 1$. This result implies that the original dimensionality is irrelevant as far as the distance preservation is concerned. What matters is the number of points that get projected and the accuracy with which we want to preserve the distances. An important thing to note is that the bounds provided by Johnson-Lindenstrauss are rather loose, and in practice the number of dimensions to project to in order to preserve the relevant distances may be much lower. The original result of Johnson & Lindenstrauss was an existence result that did not say how to get the linear transform. Later work by Dasgupta has shown that certain random matrices fulfil the JLL guarantee with high probability, and there are several ways to generate a random projection matrix. The method used in this work is to generate a random matrix with Gaussian entries. There are certain properties of this matrix, which may help us intuitively understand this: Any two rows in the random projection matrix are approximately orthogonal to each other, and have approximately the same length. In essence the random projection is an approximate Isometry. Thus, there is no need to normalize the vector to unit length or to orthogonalise the random projection matrix in practice.

The following are the steps to reduce the dimensionality of the data by random projections:
Suppose that we have a data set $X = \{X_1, X_2, ...X_n\}$ where each data point is a p dimensional vector such that X_i is a subset of Rp and we need to reduce the data to a q dimensional space such $1 < q < p$ that,

- Arrange the data into a $p \times n$ matrix where p is the dimensionality of the data and n is the number of data points
- Generate a $q \times p$ random projection matrix R* using the MATLAB randn (q , p) function.
- Multiply the random projection matrix with the original data in order to project the data down into a random projection space

Thus we can see that transforming the data to a random projection space is a simple matrix multiplication with the guarantees of distance preservation. Hence, the random projection technique is much more efficient than PCA with a run time complexity of only O (pqn). To summarize, we can say that the RP[3][18][19][20] technique, selects random features from the weak feature set, and normalizes them between the values 0 and 1. These normalized feature sets are then equally divided into values ranging from 0 to 1 in the interval of 1/m, where m is the number of randomly selected features. These values are then assigned to each of the randomly selected features, and then the features are de-normalized by multiplying them with the max value of the given feature. This process ensures that the feature values are evenly separated, and have good variance as compared to the previously weak features Thus by passing the weak features to this technique; we are able to obtain a feature reduced set which contains only strong features. These sets are then given to the live wire algorithm for segmentation.

B. Flow chart of proposed work.

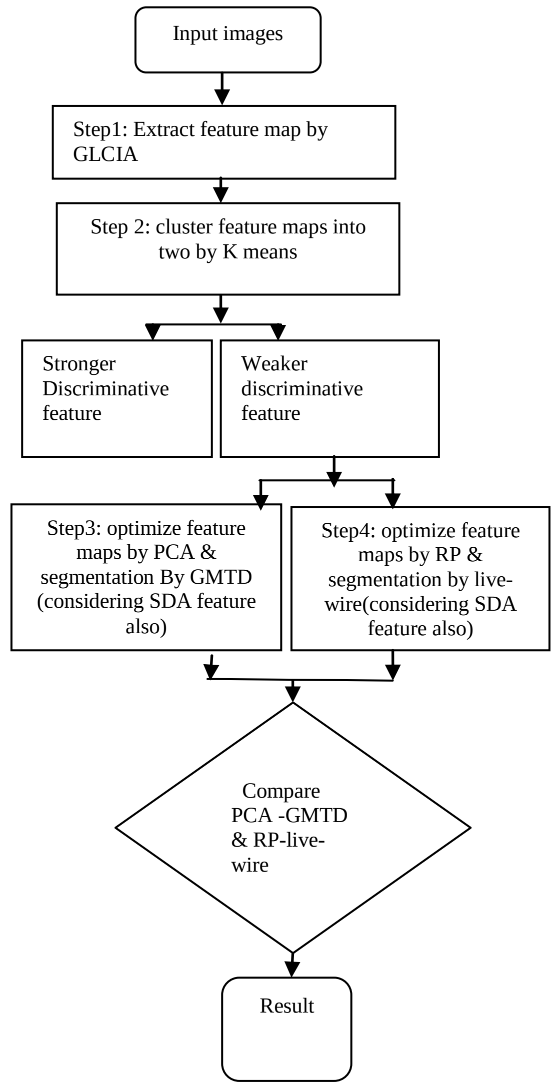

Figure 1. Overall flow of the system

C. Proposed Live-Wire segmentation algorithm

Both the strong and the weak features are given to the live wire algorithm. The live wire algorithm works in the following steps,

- The input image is converted into a hyper complex representation using a quaternion function
- The pixels of this converted image are evaluated for entropy

- Pixels with highest entropy are selected and a resultant image is formed
- This image is iterated N times into a Gaussian filter unit in order to smoothen the image
- The smooth image is given to a border cut block in order to obtain sharp borders for the segmented image
- This sharp image is again smoothened using Gaussian filter to obtain a final live wire image mask

The resultant live wire image mask is multiplied with the input image in order to get the final live wire image Livewire is a graph-based method for interactive image segmentation. This necessitates the generation of an undirected weighted-graph W from an input image. Any n-dimensional image can be represented as an undirected graph. The graph nodes represent the image pixels. The edges represent the connections/relationships between the neighbouring pixels. We use a 4-connectivity model where every pixel is connected to four of its closest neighbouring pixels, that is, the top, and bottom, left and right pixels. Subsequently, we assign the weights to the graph edges. The weights assigned are a function of the edge strength between two pixels. More specifically, for each pixel $p_{i,j}$ image derivatives/gradients G_x and G_y are calculated along the horizontal and the vertical directions, such that,

$$G_x = p_{i,j} - p_{i+1,j} \quad (1)$$

$$G_y = p_{i,j} - p_{i,j+1} \quad (2)$$

The magnitude G and direction θ of the gradient are calculated using normal Cartesian to polar conversion formula as follows,

$$G = \sqrt[2]{(G_x)^2 + (G_y)^2} \quad (3)$$

$$\theta = tan^{-1}\frac{G_y}{G_x} \quad (4)$$

The orientation θ calculated from the Equation 4 is normal to the image edge. Since, the objective of a Livewire algorithm is to follow along an image edge/boundary; therefore, the recovered directional vector θ is rotated through ninety degrees to align with the edge. We will refer to the re-aligned vector a θ^a for the current project, we followed the convention of rotating the vector θ clockwise. An anti-clockwise rotation yields the same results. The re-aligned vector θ^a may have any orientation between 0 degrees and 360 degrees with reference to the horizontal. On the other hand, the edges connecting a pixel $p_{i,j}$ with its neighbours occur only along the orientations of 0, 90, 180 and 270 degrees, therefore, the re-oriented gradient vector with the orientation θ^a and magnitude G is decomposed to its horizontal and vertical components G_x^a and G_y^a . These components are shown in the Equations 5 and 6,

$$G_x^a = G\cos\theta^a \quad (5)$$

$$G_y^a = G\sin\theta^a \quad (6)$$

The inverse of these components G_x^a and G_y^a are assigned as the edge weights W_x and W_y in the cost graph W . The inverse is calculated so that the strongest edges in the image have lowest cost in W, and vice versa.

$$W_x = \frac{1}{G_x^a} \quad (7)$$

$$W_y = \frac{1}{G_y^a} \quad (8)$$

The process is repeated for all the pixels in an image. Given an undirected weight graph W , the goal of Livewire is to find the strongest edge between two user specified control points C_k and C_{k+1}. The stronger the edge strength in the image I, the lower its weight in W, therefore, the task of finding the strongest edge between points C_k and C_{k+1} is the same as finding the lowest cost path (i.e., the shortest path) between the nodes representing the fore-mentioned control points in the graph W. We use the Dijkstra's algorithm for finding this path. Therefore, given an ordered set of control points C_1, C_2, C_3, ... C_k, ... C_n, a connected curve can be generated by finding the shortest path between all pairs of neighbouring control points, that is, a set of n points would generate a set of $n-1$ paths. These paths are connected together to generate the resultant curve. The generated curve may or may not be closed. The goal of an image segmentation algorithm is to generate a closed delineating curve which separates the foreground and the background pixels. This generates a closed curve and also outputs the final resultant image from the given input image under test. This resultant live wire image is then compared in terms of features from the strong and weaker feature sets, and matching of every feature set is obtained. The feature sets of the input image which matches the stronger feature sets of the live wire image are selected and produced at the output, while the other feature sets which do not match the live wire image are masked out of the output image. This obtained output image is then compared with a standard segmented image in order to evaluate the accuracy of segmentation. The proposed live wire based segmentation algorithm has many advantages.

III. EXPERIMENTAL RESULT

We first implemented PCA with the GMTD [2],[26] segmentation algorithm and compared it with random projection technique, and obtained the following results for multiple types of images[42] from Brodatz dataset.

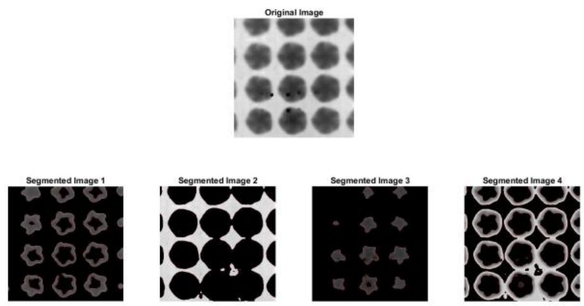

Figure 1. (a). Output with PCA+GMTD

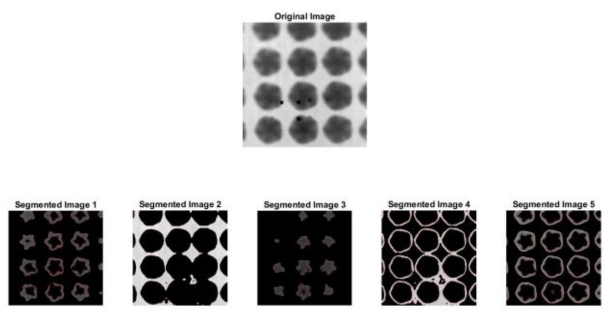

Figure 1.(b). Output with RP+GMTD

For simple textures, random projection gives better number of segments, and thus should be used when the textures are simple enough.

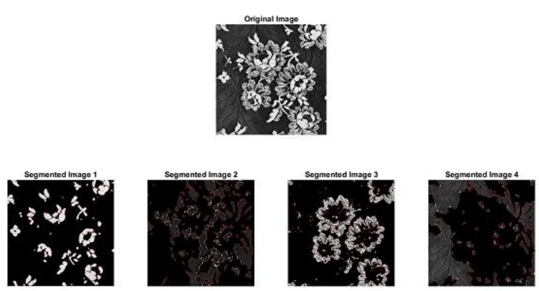

Figure 2.(a). Output with PCA+GMTD

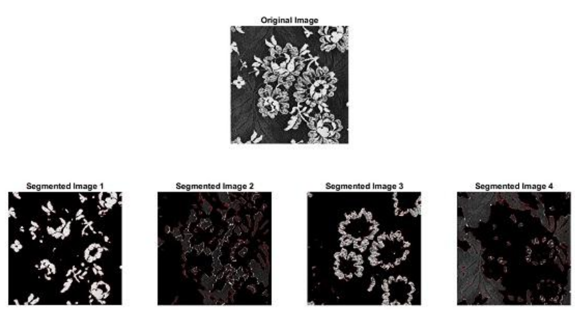

Figure 2.(b). Output with RP+GMTD

For single object textures, random projection gives same number of segments when compared with RP and GMTD, and thus for single objects both methods are equally capable of producing good results.

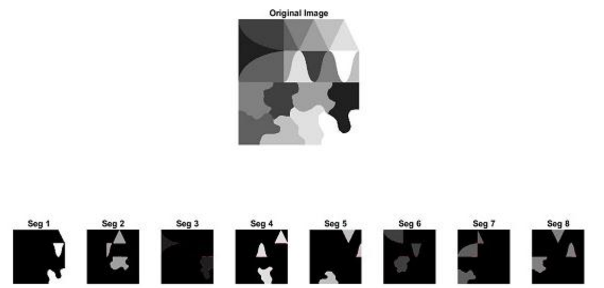

Figure 3. (a). Output with PCA+GMTD

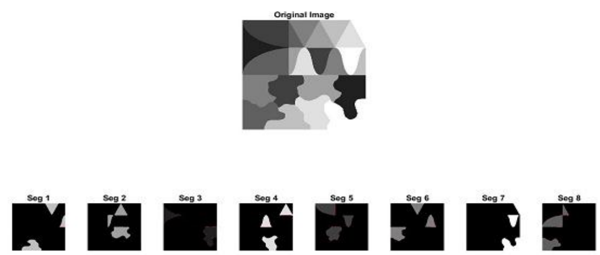

Figure 3.(b). Output with RP+GMTD

For multiple textures, random projection when combined with PCA gives same number of segments when compared with RP and GMTD, and thus for multiple textures both methods are equally capable of producing good results

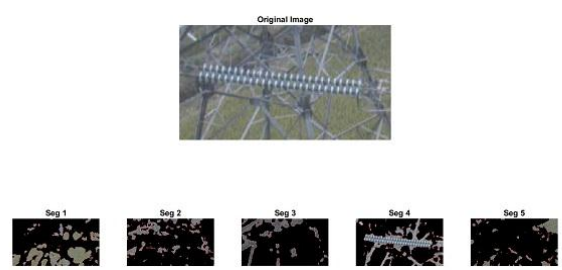

Figure 4. (a). Output with PCA+GMTD

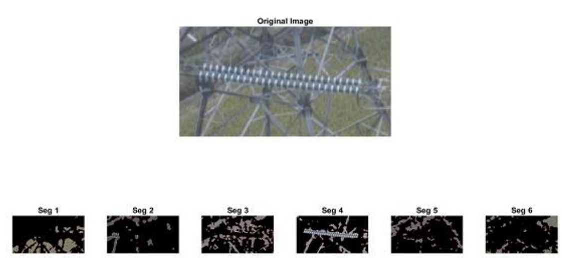

Figure 4.(b). Output with RP+GMTD

For single object textures, random projection when combined with PCA gives better number of segments as compared to

PCA with GMTD, and thus RP should be used when there is single object segmentation problem.
We evaluated the results for the proposed algorithm, and obtained the following outputs,

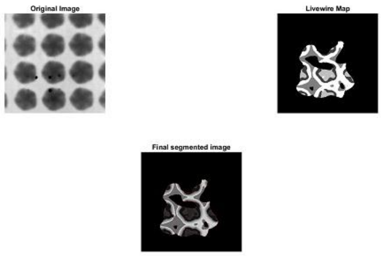

Figure 5. Live wire with simple textures

In simple texture cases, the proposed algorithm produces the region of interest which contains the unique texture at the output, and thus can be considered as a good segmentation technique.

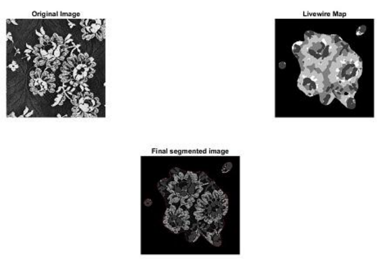

Figure 6. Live wire with Single texture object

For single texture objects, the results obtained from the LW algorithm are astonishing. It carefully segments out the region of interest from the input image and produces the final segmented regions at the output. Smaller details are also included, like in figure 6, we can observe that the overall petals of the flower are segmented out along with the minor up right and bottom left regions from the image under test.

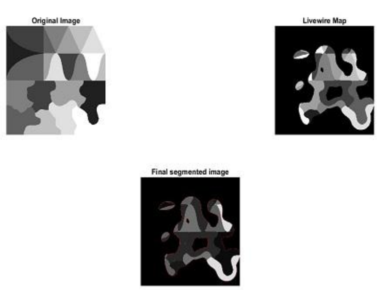

Figure 7. Live wire with Multiple complex textures

Complex textures are also detected and the key points are extracted at the output with the LW algorithm

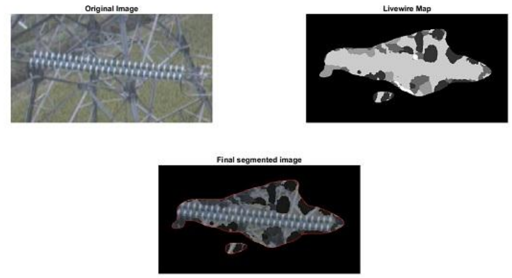

Figure 8. Live wire with single object

Single object detection is also done with good accuracy in the live wire algorithm. The single object detection output shows promising results by segmenting out the proper region of interest from the input images.

By these comparisons we are able to conclude that our segmentation results are visually more appealing than the other standard methods. We also evaluated the delay and precision of the proposed system, and compared it with the existing standard algorithms. The results can be shown as follows.

Table 1. Comparison of delay between various methods

Image Type	No. of images	Delay RP+GMTD (s)	Delay PCA+GMTD (s)	Delay Proposed RP+LW (s)
Single Texture	10	2.665	3.871	2.247
Single object	15	2.854	3.913	2.258
Complex Texture	20	3.374	4.895	2.618
Object of interest	30	2.514	3.227	1.952

The following graph demonstrates the results in a more visually recognizable format,

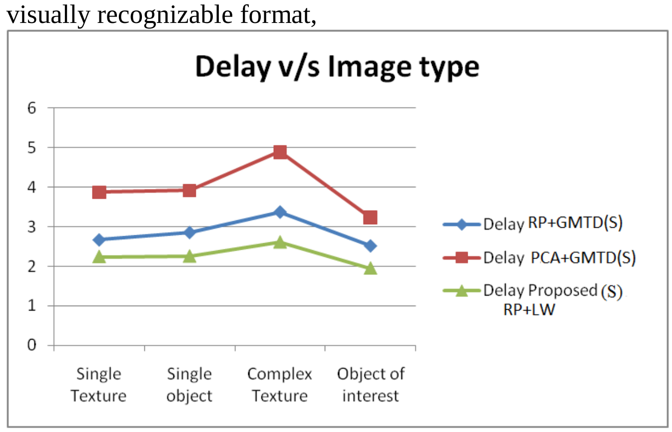

Figure 8. Delay graph

From the delay graph it is very clear that the live wire algorithm reduces the delay of computation when compared with the other algorithms, this is due to the fact that the live wire technique has a faster feature extraction method namely random projection, and due to the bounding curve properties of the LW algorithm, it takes less time to parse the images and thereby reduces the overall delay for image segmentation. Next we compare the precision of the proposed live wire algorithm with the same techniques and observe it's results.

The following table demonstrates the precision of segmentation between different algorithms,

Table 2. Comparison of precision for various algorithms

Image Type	No. of images	Precision PCA+GMTD (%)	Precision RP + GMTD (%)	Precision Proposed RP+LW (%)
Single Texture	10	78.2	81.5	87.6
Single object	15	88.4	89.1	91.8
Complex Texture	20	77.9	80.2	90.7
Object of interest	30	83.6	87.4	95.2

The number of correct pixels presented at the output is calculated by finding the intersection between the output segmented image and the ground truth image, and the number of pixels found in the intersection are marked at number of correct pixels presented at the output, and then it is divided by the total number of corrected pixels to finally get the precision value. The precision graph can be shown as follows,

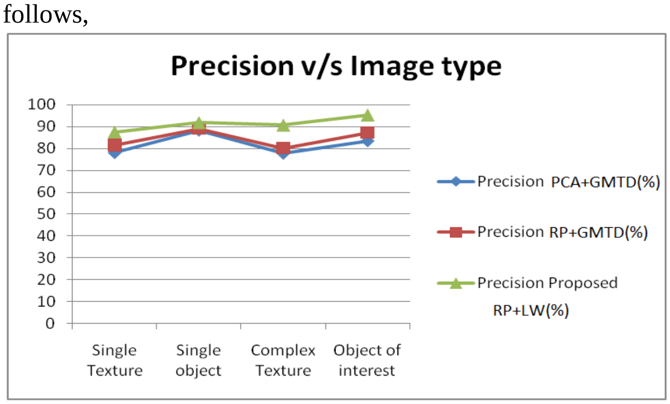

Figure 9. Precision graph

The improvement in precision is shown by the following figure, where the proposed precision is kept as a reference and the other precision values are compared with it, the figure clearly indicates that the proposed precision value is much higher when compared to the other standard methods, which is also seen by the results,

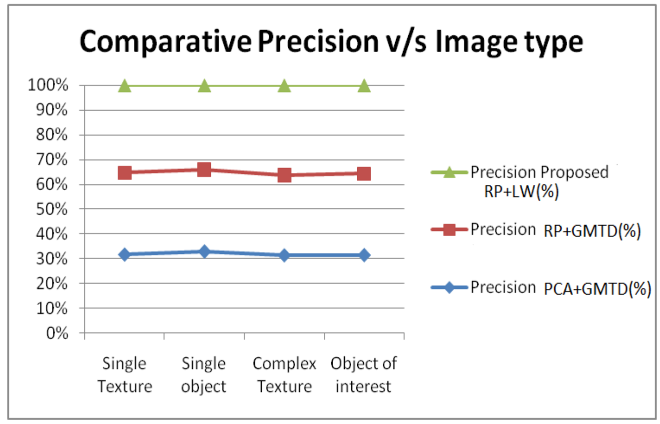

Figure 10. Comparative precision values

The next section picks out some very interesting observations and also shows some possible future work which can be performed by researchers to further improve the segmentation quality.

IV. CONCLUSION

In our proposed research work, the application of live-wire algorithm has been proposed to segment complex Aerial insulator images along with RP algorithm to extract the features of images. It contains two aspects: the optimization of texture features and segmentation. We first divide the extracted texture features into two categories: one with the stronger discriminative ability and the other with weaker ability. Random projection is partially employed to optimize the second category to better distinguish the different texture objects having low contrast. Then, live wire is use to fast segmentation as well as improves weight parameter. In addition, two fast methods of GLCIA and dual formulation have been adopted to speed up the computation of the GLCM based texture features and to overcome the drawbacks of the usual gradient descent flow methods, respectively. The proposed technique will solve the problems of improve weight parameter and feature extraction with RP.

From result we conclude following findings-

- Better texture extraction than other technique like PCA,MRF
- Random projection is computationally faster than PCA due to random selection of ‘best’ basis vector which improves the computational speed of RP.
- Improve weight parameter which leads to improve segmentation.
- Expecting fast segmentation because of RP_live wire algorithms.
- Live-Wire segmentation algorithm is an interactive tool for efficient, accurate and reproducible boundary extraction which requires minimal user input

V. FUTURE SCOPE

In future, researchers can implement machine learning and artificial intelligence based algorithms like Q-Learning, Reinforcement learning and deepness in order to further improves the accuracy of precision and reduces the error rate in the system. Researchers may also try for parallel processing and pipelining techniques and multi-processor hardware implementation using FPGAs or ASICs

REFERENCES

[1] Gonzalez Book "Digital Image Processing",(3rd edition)

[2] Qing gang Wu, Jubai An, and Bin Lin "A Texture Segmentation Based On PCA & Global Minimization Active Contour Model For Aerial Insulator Images" IEEE journal of selected topics in applied earth observations and remote sensing accepted April 11,2012.

[3] Li Liu and Paul W. Fieguth, Member, IEEE "Texture Classification from Random Features", IEEE transactions on pattern analysis and machine intelligence, vol. 34, no. 3, march 2012

[4] D. A. Clausi, "Comparison and fusion of co-occurrence, Gabor and MRF texture features for classification of SAR sea-ice imagery,"Atmos.-Ocean, vol.39, no.3, pp. 183–194, 2000.

[5] automatic recognition of human settlements in arid regions with scattered vegetation," IEEE J. Sel. Topics Appl. Earth Observ.Remote Sens. (JSTARS), vol. 4, no. 1, pp. 16–26, 2011

[6] P. R. Chowdhury, B. Deshmukh, A. K. Goswami, and S. S. Prasad, "Neural network based dunal landform mapping from multispectral images using texture features," IEEE J. Sel. Topics Appl. Earth Observ.Remote Sens. (JSTARS), vol. 4, no. 1, pp. 171–184, 2011.

[7] A. A. Ursani, K. Kpalma, C. C. D. Lelong, and J. Ronsin, "Fusion of textural and spectral information for tree crop and other agricultural cover mapping with very-high resolution satellite images, "IEEEJ.Sel.Topics Appl. Earth Observ.Remote Sens. (JSTARS) ,vol. , no1 , pp.225–235, 2012.

[8] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification, " IEEE Trans. Syst., Man, Cybern., vol. 3, no. 6, pp. 610–621, 1973.R. F. Walker, P. T. Jack way, and D. Long staff, "Genetic algorithm optimization of adaptive multiscale GLCM features," Int. J. Pattern Recogn. Artificial Intell., vol. 17, no. 1, pp. 17–39, 2003.

[9] D.A. Clausi and Y. Zhao, "Grey Level Co-occurrence Integrated Algorithm (GLCIA): A superior computational method to rapidly determine co-occurrence probability texture features," *Comput. Geosci.*, vol. 29,no. 7, pp. 837–850, 2003.

[10] R.F.Walker, P. T. Jackway, and D. Longstaff, "Genetic algorithm optimization of adaptive multiscale GLCM features," *Int. J. Pattern Recogn. Artificial Intell*, vol. 17, no. 1, pp. 17–39, 2003.

[11] W.B. Johnson and J. Lindenstrauss, "Extensions of Lipschitz Mappings into a Hilbert Space," Proc. Conf. Modern Analysis and Probability, pp. 189-206, 1984.

[12] S.Dasgupta and A. Gupta, "An Elementary Proof of a Theorem of Johnson and Lindenstrauss," Random Structures and Algorithms, vol. 22, no. 1, pp. 60-65, 2003.

[13] E.Bingham and H. Mannila, "Random Projection in Dimensionality Reduction: Applications to Image and Text Data," Proc. Seventh ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining, pp. 245-250, 2001.

[14] S.Dasgupta, "Experiments with Random Projections," Proc. 16th Conf. Uncertainty in Artificial Intelligence, pp. 143-151, 2000.

[15] X.Z. Fern and C.E. Brodley, "Random Projection for High Dimensional Data Clustering: A Cluster Ensemble Approach," Proc. 20th Int'l Conf. Machine Learning, 2003.

[16] E.J. Cande`s and T. Tao, "Decoding by Linear Programming" IEEE Trans. Information Theory, vol. 51, no. 12, pp. 4203-4215, Dec. 2005.

[17] E.J. Cande`s and T. Tao, "Near-Optimal Signal Recovery from Random Projections: Universal Encoding Strategies?" IEEE Trans. Information Theory, vol. 52, no. 12, pp. 5406-5425, Dec. 2006.

[18] D.L.Donoho, "Compressed Sensing," IEEE Trans. Information Theory, vol. 52, no. 4, pp. 1289-1306, Apr. 2006.

[19] G. Biau, L. Devroye, and G. Lugosi, "On the Performance of Clustering in Hilbert Spaces," IEEE Trans. Information Theory,vol. 54, no. 2, pp. 781-790, Feb. 2008.

[20] R.G. Baraniuk, M. Davenport, R.A. DeVore, and M. Wakin, "A Simple Proof of the Restricted Isometry Property for Random Matrices," Constructive Approximation, vol. 28, no. 3, pp. 253-263,2008.

[21] D.Achlioptas, "Database-Friendly Random Projections," Proc. 20th ACM Symp. Principles of Database Systems, pp. 274-281, 2001.

[22] N. Goel, G. Bebis, and A. Nefian, "Face Recognition Experiments with Random Projection," Proc. SPIE, vol. 5779, pp. 426-437, 2005.

[23] Li, ping, Trevor J Hastie and Kenneth W. Church "Very sparse random projection" Proceedings of 12th ACM SIKDD international conf.on knowledge discovery and data mining ACM 2006.

[24] P.A.Maturkar, Dr.M.A.Gaikwad "RP-live wire algorithms" Proceeding of by IEEE explorer digital library International Conference On "Power, Control, Signals and Instrumentation Engineering (ICPCSI-2017),pp. 74-78 dt. 21st & 22nd Sept. 2017

[25] P.A.Maturkar, Dr.M.A.Gaikwad "Texture Feature Optimization of complex Images using RP&PCA and segmentation by GMTD" Proceeding by IEEE International conference on "Resent innovation in Electrical, Electronics & communicationEngineering-ICRIEECE-2018", Bhubaneswar, Dt.27th & 28th July 2018

[26] Xiao-Feng Wang, Hai Min, Yi-Gang Zhang, "Multi-scale local region based level set method for image segmentation in the presence of intensity in homogeneity", Elsevier March 2015 Wanceng Zhang, Xian Sun, Hongqi Wang, Kun Fu, "A generic discriminative part-based model for geospatial object detection in optical remote sensing images", Elsevier January 2015.

[27] Wanceng Zhang, Xian Sun, Hongqi Wang, Kun Fu, "A generic discriminative part-based model for geospatial object detection in optical remote sensing images", Elsevier January 2015.

[28] Jian Yang, Peijun Li, Yuhong He, "A multi-band approach to unsupervised scale parameter selection for multi-scale image segmentation", Elsevier August 2014.

[29] Jing Liu, Peijun Li , Xue Wang, "A new segmentation method for very high resolution imagery using spectral and morphological information", Elsevier March 2015.

[30] Zhijian Huang, Jinfang Zhang, Fanjiang Xu, "A novel multi-scale relative salience feature for remote sensing image analysis", Elsevier January 2014

[31] Chao Wang, Ai-Ye Shi, Xin Wang and et al., "A novel multi-scale segmentation algorithm for high resolution remote sensing images based on wavelet transform and improved JSEG algorithm", Elsevier October 2014.

[32] Xiang-Yang Wang, Xian-Jin Zhang and et al., "A pixel-based color image segmentation using support vector machine and fuzzy C-means", Elsevier September 2012.

[33] Jorge E. Patino, Juan C. Duque ,"A review of regional science applications of satellite remote sensing in urban settings", Elsevier January 2013.
[34] Zhongwu Wang, John R. Jensen, Jungho Im, "An automatic region-based image segmentation algorithm for remote sensing applications", Elsevier October 2010.
[35] Jianqiang Gao, Lizhong Xu ,"An efficient method to solve the classification problem for remote sensing image", Elsevier January 2015.
[36] Saman Ghaffarian, Salar Ghaffarian, "Automatic histogram-based fuzzy C-means clustering for remote sensing imagery", Elsevier November 2014.
[37] Xueliang Zhang, Pengfeng Xiao, Xiaoqun Song, Jiangfeng She, "Boundary-constrained multi-scale segmentation method for remote sensing images", Elsevier April 2013.
[38] Stelios K. Mylonas, Dimitris G. Stavrakoudis, John B. Theocharis ,"GeneSIS: A GA-based fuzzy segmentation algorithm for remote sensing images", Elsevier December 2013.
[39] Xueliang Zhang, Pengfeng Xiao and et al., "Hybrid region merging method for segmentation of high-resolution remote sensing images", 2014.
[40] Maire, M.; Fowlkes, C.; Malik, J.; "Contour Detection and Hierarchical Image Segmentation", IEEE 2011.
[41] Jianyu Chen, Delu Pan, Qiankun Zhu and et al., "Edge-Guided Multi scale Segmentation of Satellite Multispectral Imagery", IEEE 2012.
[42] P. Brodatz, *Texture – A Photographic Album for Artists and Designers*. New York: Reinhold, 1968.
[43] A.H.M. Jaffar Iqbal Barbhuiya, K. Hemachandran "Hybrid Image Segmentation Model using KM, FCM, Wavelet KM and Wavelet FCM Techniques"Vol.6, Issue.9, pp.315-323, Sep-2018
[44] S. Pathak, V. Sejwar "A Review on Image Segmentation Using Different Optimization Techniques"Vol.5 , Issue.5 , pp.217-221, May-2017

Authors Profile

Pradnya Maturkar did her BE in Electronics Engineering in 2002.& M.Tech degree in Electronics Engineering in 2011 from Rashtra Sant Tukodoji Maharaj Nagpur University, India. She has received the M.C.M degree in 2007 f She was worked as Asst. Professor at Yeshwantrao chavan college of Engineering. She is currently working as Asst. Professor at RGCER, Nagpur.She is pursuing her Ph.D. degree from RTM, Nagpur university. Her research interests include remote sensing image processing, image segmentation, edge detection, pattern recognition, and computer vision. She has published her book "Digital communication" in July 2013 & has received copyright for "Wireless Communication". She has life Member (LM) of ISTE. She has around 17 publications on his credit in Journals, International & National.

Dr. Mahendra Gaikwad did his BE in Electronics Engineering in 1991 from Nagpur University by securing Second Merit position in the Nagpur University & First Merit position in the College. Later he did his MBA in Marketing Management from Nagpur University and he has completed his MCM from Nagpur University. He did his Master's Degree in Personal Administration from Nagpur University. He did his M.Tech in Communication Engineering from Indian Institute of Technology (IIT), Bombay in 1998. He did his PhD on "Network -on-Chip Architecture using Perfect Difference Network Topology" from VNIT, Nagpur. He was worked as Principal & Professor at B. D. College of Engineering, Sevagram. Presently he is working as Professor at G. H. Raisoni College of Engineering, Nagpur He has published 100 research papers in various International and National Journals, International and National Conference, Seminar, Symposium.

