A Robust Adaptive Multi-Scale Superpixels Segmentation in SEM Image

R. Susithra, A. Mahalakshmi, Judith Justin

Abstract--- ***This work presents a region-growing image segmentation approach based on superpixels SEM Image segmentation decomposition. From a first contour- constrained over-segmentation of the input image, the image segmentation into parts is achieved by again and again merging like superpixels SEM image segmentation into parts into fields, regions. This approach raises two key issues: how to compute the similarity between superpixels SEM Image segmentations in order to perform accurate merging and in which order those superpixels SEM Image segmentations must be merged together. In this perspective, we firstly introduce a robust adaptive multi-scale superpixels SEM Image segmentation similarity in which region comparisons are made both at content and common border level. Secondly, we offer a complete merging worked design to small amount of support guide the field, region merging process. Such strategy uses an adaptive merging criterion to ensure that best region aggregations are given highest priorities. This lets to get stretched to a final segmentation into harmony regions with strong division line take as rule. We act experiments on the BSDS500 image dataset to high-light to which extent our method compares favorably against other well-known image segmentation algorithms.***

Keywords--- ***Scanning Electron Microscope (SEM), adaptive multi scale superpixel, image segmentation.***

I. INTRODUCTION

Image segmentation is a fundamental task in many pattern recognition and computer vision applications such object detection, content-based image retrieval and medical image analysis. Segmentation is the process that consists of partitioning an image into homogeneous regions of pixels with similar characteristics and spatiallyaccurate boundaries. Despite the simplicity of its definition, image segmentation is a hard problem that does not have a universal solution. Beside, one should not expect the segmentation of an image to be unique because of at least two reasons, according to Zhuowen: it is fundamentally complex to model the vast amount of visual patterns of images, perception is intrinsically ambiguous. Indeed, quite often one can provide different logical interpretations for the same image. Image segmentation is a field that has been extensively studied for decades and the existing methods can

be classified into clustering-based, boundary-based and region-based, Clustering-based methods segment images by classifying pixels based on their extracted properties, Boundary-based methods use the assumption that pixels properties change abruptly between different regions, Region-based methods assume that a region is composed of adjacent pixels with similar properties, There are some hybrid approaches that combine two or more of the aforementioned methods.

Region-growing is a popular region-based segmentation technique that operates by merging regions with similar pixels on their borders in an iterative fashion. At each iteration, all pixels that border the growing region are examined and the most similar are appended to that region. Initial regions may be pixels or regions produced by dedicated over-segmentation techniques, in which case they are called superpixel A superpixels SEM Image segmentation is commonly defined as a perceptually meaningful atomic region obtained by aggregating neighboring pixels based on spatial and appearance similarity criteria. In recent years, superpixels SEM Image segmentation-based image segmentation techniques have gained a big interest among the image processing community mainly for their computational efficiency..Super pixels SEM Image segmentations also allow more efficient semantic feature extraction contrary to image patches. However, those techniques present two main issues: the similarity measure between superpixels SEM Image segmentations and the superpixels SEM Image segmentations dependencies. The similarity measure refers to the quantification of how similar two super pixels SEM Image segmentations are. This is usually computed by a normalized distance between the super pixels SEM Image segmentations. Mehnert and Jackway[14] stated that a region-growing algorithm is inherently dependent on the processing order of the image pixels. Either, whenever several pixels have the same distance from their neighboring pixels or whenever one pixel has the same distance from several regions. As a solution for the aforementioned issues, we propose in this work a robust similarity measure between superpixels SEM Image segmentations as well as adaptive superpixels SEM Image segmentation merging strategy. The similarity measure integrates content and border information jointly to provide robust similarity between superpixels SEM Image segmentations. The merging strategy uses an auto updated criterion to iteratively aggregate superpixels SEM Image segmentations based on the proposed similarity measure.

II. RELATED WORK

A. Simple Linear Iterative Clustering

A superpixels SEM Image segmentation decomposition of an image consists of a partition of the image into small perceptually meaningful regions. They provide a handy representation of the image that heavily reduces the number of visual primitives. According to Stutz et al. any superpixels SEM Image segmentations over-segmentation algorithm

Manuscript received February 01, 2019

R. Susithra, PG Scholar, Avinashilingam Institute for Home Science and Higher Education for Women. Coimbatore, Tamil Nadu (e-mail:susirraj@gmail.com)

A. Mahalakshmi, Research Scholar, Avinashilingam Institute for Home Science and Higher Education for Women. Coimbatore, Tamil Nadu (e-mail: magaa811@gmail.com)

Dr. Judith Justin, Professor and Head School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women. Coimbatore, Tamil Nadu (e-mail: hodbmieau1@gmail.com)

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

should fall in one of the seven following categories: watershed-based, density-based, graph-based, contour-based, path-based, clustering-based and energy optimization. Simple Linear Iterative Clustering (SLIC) is a clustering-based algorithm and one of the most commonly used to generate superpixels SEM Image segmentations. It offers a simple implementation and provides compact and nearly uniform superpixels SEM Image segmentations. The cluster centers are initialized on a uniform grid and pixels in a 2S × 2S window around clusters are iteratively aggregated according to the metric defined in a five-dimensional space composed by three features and two spatial components.

B. Superpixels SEM Image Segmentation

Superpixels SEM Image segmentations over-segmentations are usually used as an initilization for image segmentation for two main reasons. Firstly, they generally adhere to boundaries and produce meaningful small re-gions. Secondly, they drastically reduce computation time by reducing the number of processed elements. Hsu and Ding proposed a segmentation approach for natural images that uses simple Linear Iterative Clustering (SLIC)[]as superpixels SEM Image segmentation generation technique. They first regroup superpixels SEM Image segmentations by a spectral clustering algorithm into clusters and then perform a merging step using cluster similarities. Another work from Yang et al. presented a kernel fuzzy similarity measure which is used to cluster superpixels SEM Image segmentations. A 10-dimensional texture-based feature vector is extracted to characterize each superpixels SEM Image segmentation. After clustering, a k-means final step is applied to group clusters into final regions. Yu and Wang proposed a graph-based coarse and fine merging strategy based on features extracted on superpixels SEM Image segmentations including three Gestalt laws- inspired rules to model the superpixels SEM Image segmentation context. In the same vein, the work of Oneata et al proposed a segmentation algorithm for action and event detection in videos. Similarity between regions is computed based on appearance, motion and geodesic spatio-temporal features. A hierarchical clustering with average linkage is then applied on the graph to produce the final segmentation result.

In all these works, we can note that superpixels SEM Image segmentations to be merged are assumed to satisfy two main criteria: spatial adjacency and perceptual similarity. This implies that an efficient approach should be able to pick the most similar spatial neighbor of a superpixels SEM Image segmentation in both local and global manners. In this paper, we present a region-growing segmentation approach that uses superpixels SEM Image segmentations over-segmentation as input data. We propose a robust similarity measure between superpixels SEM Image segmentations that efficiently combine content and border scale to provide an accurate measure. Moreover, we define a merging strategy to guide the region growing process through an adaptive merging criterion and a priority order between region aggregations.

C. Proposed superpixels SEM Image segmentation

As initialization, the proposed approach segments the source image into connected superpixels SEM Image segmentations using the SLIC algorithm. SLIC is popular since it allows to generate superpixels SEM Image segmentations with simple implementation, fast execution and quite good accuracy. However, it can be observed that it sometimes fails to perfectly adhere to image boundaries. Consequently, global contour constraints are applied on the SLIC algorithm to overcome this issue. Once an accurate superpixels SEM Image segmentation decomposition is obtained, the iterative superpixels SEM Image segmentations growing occurs. In particular, superpixels SEM Image segmentations are grouped into regions according to two main criteria: mutual selection and global contour cross. Each region chooses the best merging candidate superpixels SEM Image segmentation from its adjacent neighbors using a robust similarity measure based on appropriate superpixels SEM Image segmentation features. Afterwards, each couple of a merging region and its neighbor superpixels SEM Image segmentation that have mutually chosen each other with enough similarity and which are not separated by a global contour are grouped together. This iterative merging process is repeated until we reach the final similarity threshold. Note that at the first loop, each single superpixels SEM Image segmentation is considered as a merging candidate region.

D. Counter constrained SLIC(CoSLIC)

Despite its efficiency, SLIC algorithm often produces superpixels SEM Image segmentations that overlap several regions on the input image boundaries. We propose to extend the SLIC algorithm by taking advantage of classical edge detectors to overcome this drawback. To this end, from the source image, global contour map are extracted using the Canny edge detector. Then, for each superpixels SEM Image segmentation, a cross check with the global contours is performed. Superpixels SEM Image segmentations that are crossed
by global contours are split along the contours into smaller superpixels SEM Image segmentations

Mutual selection and contour cross criteria ensure that each region is merged with the best super- pixel within its neighborhood at a given iteration. It produces meaningful region aggregations in the first iterations but aggregations become random as regions continue to grow. Thus, we propose an adaptive similarity threshold to introduce a notion of priority between different possible region aggregations. Indeed, the similarity threshold establishes the minimal similarity required for a region and a superpixels SEM Image segmentation to be merged. It is initially set to the maximal value and is decreased or increased depending on the results of the previous iterations. When no aggregations occurred during the previous iteration, the similarity thresh- old is decreased because it is too high to allow aggregations. On the other hand, if aggregations occurred at previous iteration, the merged regions are more likely to have strong similarity than the unchanged ones. Thus, we increase the similarity threshold to focus the aggregations on these regions. This acts as seed regions, which are expanded to achieve segmentation.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

E. Feature Extraction

The process of superpixels SEM Image segmentations growing towards accurate segmentation can be represented by a tree structure where nodes correspond to regions formed by groups of superpixels SEM Image segmentations. This hierarchical tree is constructed in a bottom-up fashion. Two similar neighbor regions are grouped into one parent region node. Given an input image I initially partitioned into a set of superpixels SEM Image segmentations SP. This definition of the region- growing approach can be expressed as a succession of ordered partitions Γk.

Regions are characterized by a concatenation of their direct descendant regions in the hierar- chical model. This describes the sequence of regions that are used to form the region and gives a multi-scale representation of the region under consideration. This idea has been initially used to represent a leaf node by a sequence of its ascendants. In the proposed approach, this idea is applied in a bottom-up way to suit our approach and keep the same outcome. Thereby, each region has a multi-level representation that contains the description of all its ordered descendants according to their level in its hierarchy. In this description space, the region BC in fig. 3-b will be characterized by FBC = (fB, fC) where FB = (f 0 , . . . , f 9) and FC = (f 0 , . . . , f 9) describing respectively the

B B C C

superpixels SEM Image segmentations B and C.

F. Merging procedure

The proposed merging procedure is inspired by the agglomerative clustering algorithm for its conceptual simplicity and flexibility. Region-growing algorithms are inherently dependent on the order of processing of the image pixels[18]. Merging order strongly affects the convergence of the approach because if two regions are wrongly merged then this error will be spread to the next steps. To tackle this issue, we propose a merging strategy that minimizes errors at each step. In fact, at a given iteration, every region makes a unique choice of merging candidates from its spatially neighboring regions. This selection ensures local optimal choice. Once each region has made its choice, a validation step performs a global optimization check to remove all regions that are not mutually chosen by each other or which are separated by a global contour. Thus, we avoid any conflicts and guarantee maximum coherence to the grouping step.

G. Adaptive merging criterion:

In classical region-growing image segmentation techniques, the compared regions belong to the same merging iteration. There is no simultaneous considerations of regions generated from differ- ent iterations. However, since the size and content of regions change through iterations, a given similarity value may not express the same visual similarity at different iterations. As an example, considering color similarity as merging criterion, a given similarity value will not correspond to the same visual similarity when comparing homogeneous small regions (early iterations) and heteroge- neous big regions (after some iterations). This means that the merging criterion value must not be a fixed value, but must be updated to remain consistent through iterations. This idea is introduced in the proposed approach by using an adaptive similarity threshold which is updated accordingly to the results of previous iteration. Basically, this threshold is decreased when no aggregations occurred at the previous iteration otherwise it is increased. In the case where no aggregation occurs at the previous iteration, the similarity threshold is too high so it is decreased to allow aggregations at the next iteration. In the opposite case, the similarity of the newly formed regions with their neighborhood will increase as their content gathers together the contents of the two regions that formed them. Thus, the current threshold is increased in order to filter irrelevant neighbor regions. The similarity threshold is updated according to the iteration coefficient (αit). By applying this adaptive similarity threshold, we ensure best region aggregations to happen first, which allows us to impose a priority order to those aggregations.

III. RESULT

The output for SEM image depending upon superpixels SEM image segmentation. It consists into trace based and density based segmentation of SEM image. The output is discussed below.

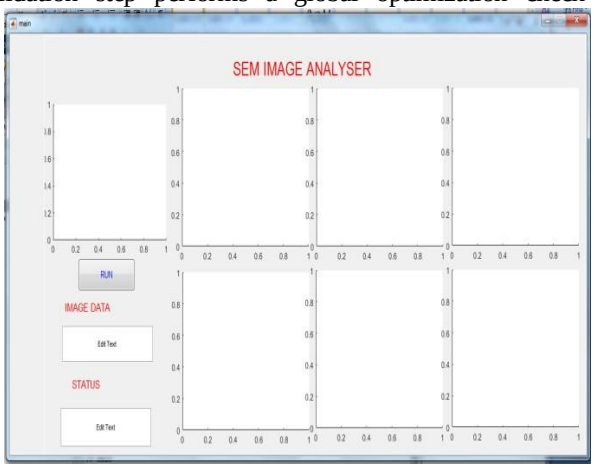

Fig. 1: Output screen

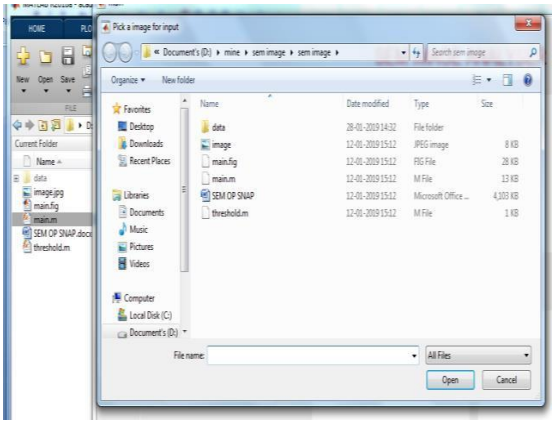

Fig. 2: Run SEM image analyzer

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

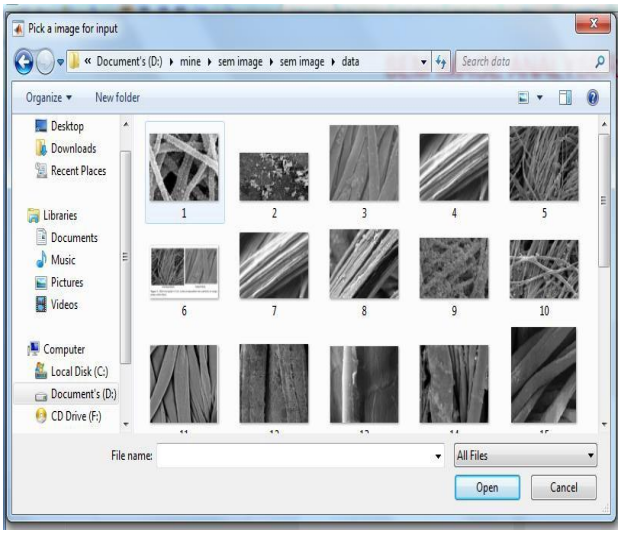

Fig. 3: Selection of Input data

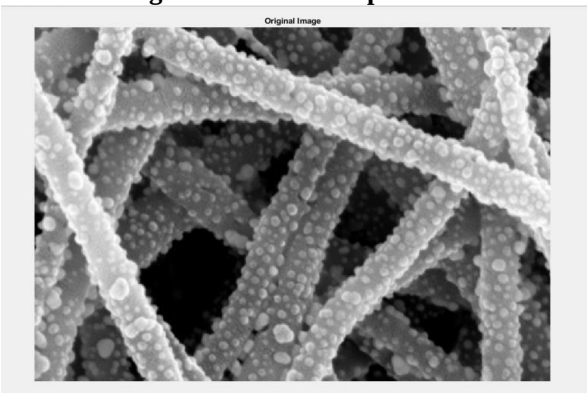

Fig. 4: Original Image

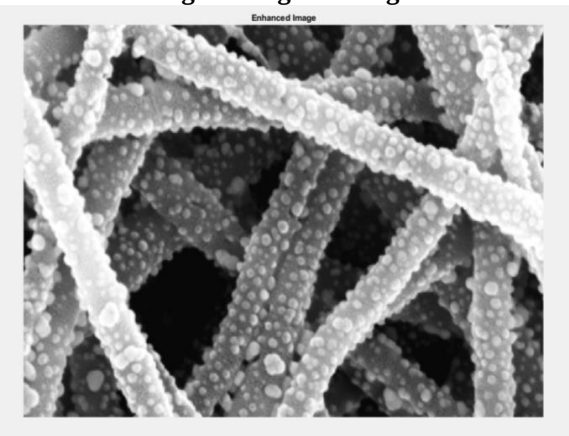

Fig. 5: Enhanced Image

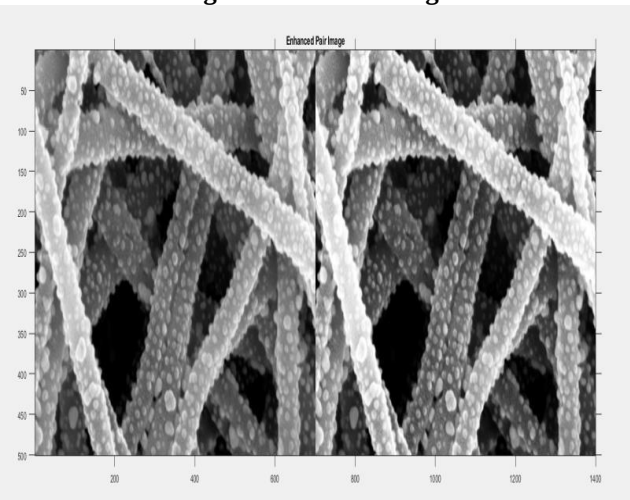

Fig. 6: Enhanced Pair Image

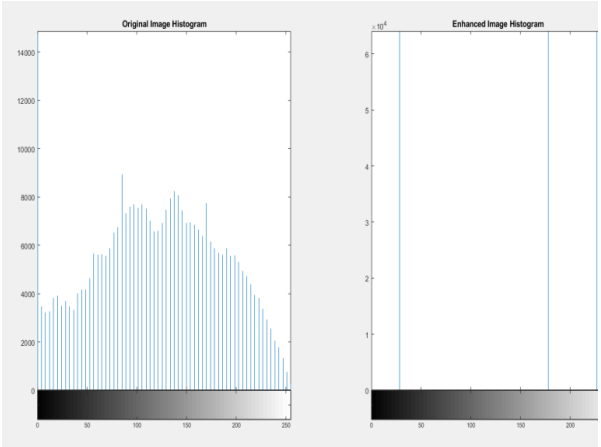

Fig. 7: Histogram of Enhanced Pair Image

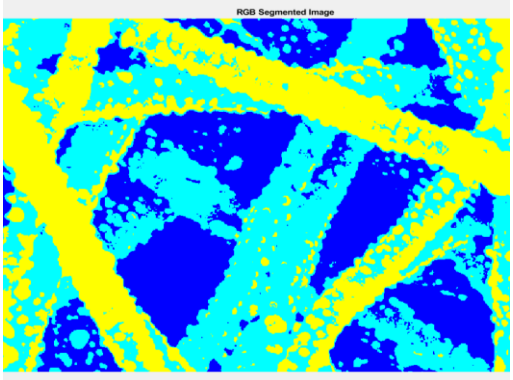

Fig. 8: RGB Segmented Image

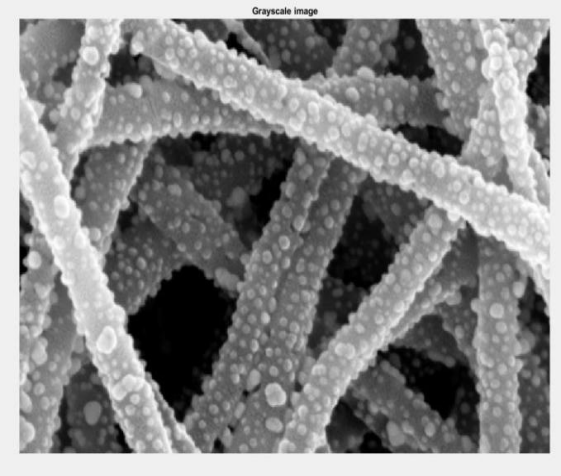

Fig. 9: Grayscale Image

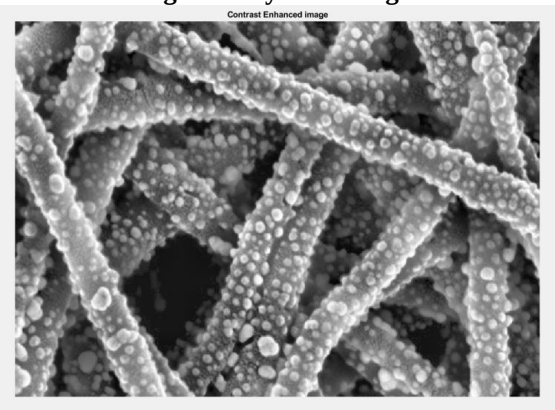

Fig. 10: Contrast Enhanced Image

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Fig. 11: Threshold Image

Fig. 12: Dot Part

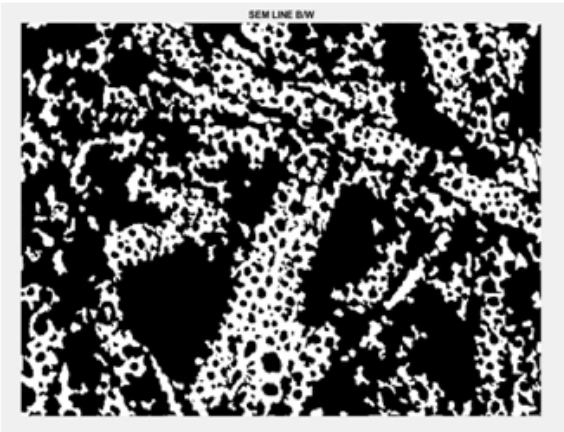

Fig 13: SEM line B/W

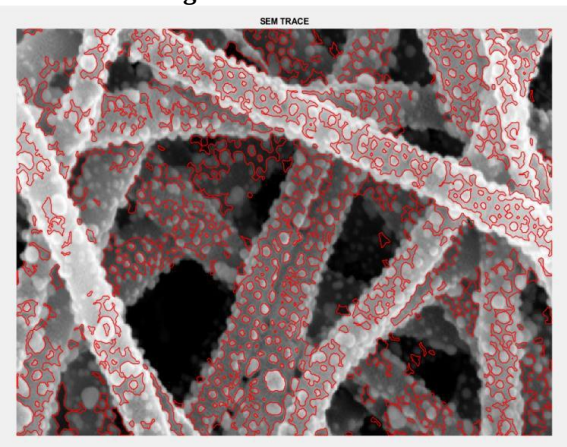

Fig. 14: SEM Trace

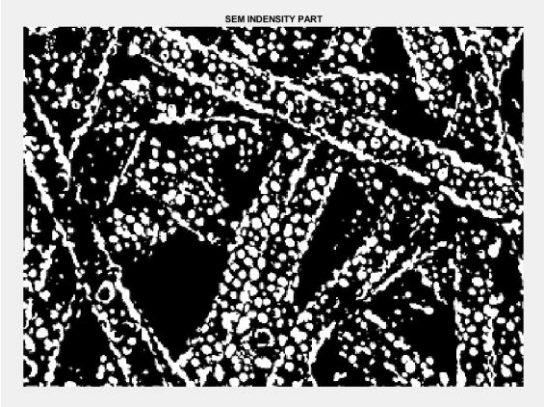

Fig. 15: SEM in density part

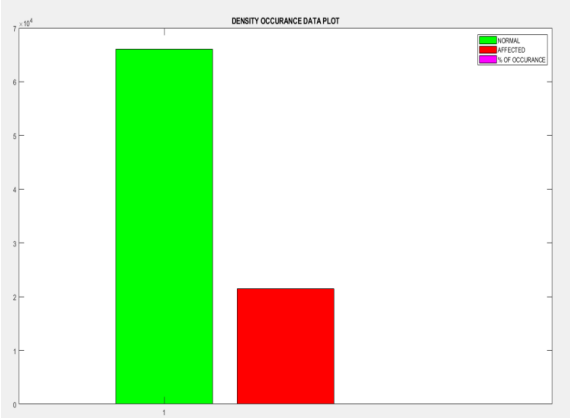

Fig. 16: Density occurrence data plot

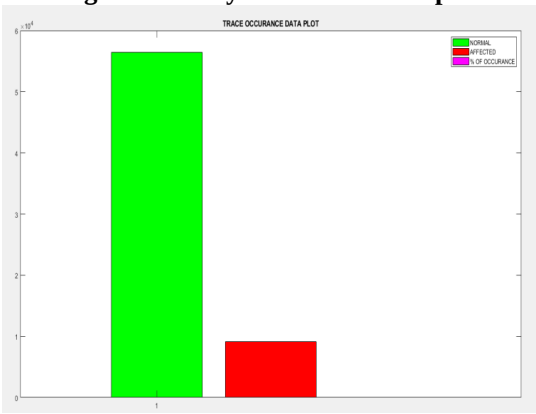

Fig. 17: Trace occurrence data plot

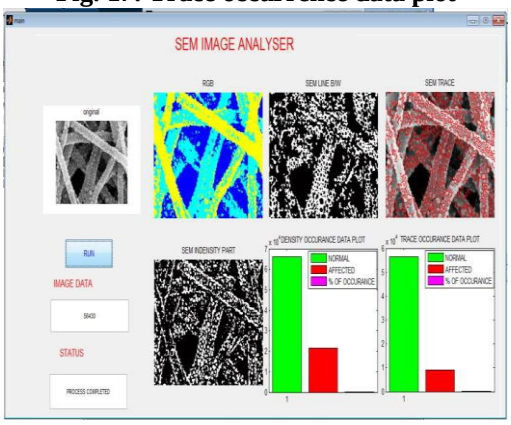

Fig. 18: Final output of SEM image analyzer

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

IV. CONCLUSION

This paper describes an image segmentation approach based on iterative superpixels SEM Image segmentation aggregation. First, an extension for the SLIC algorithm is proposed in order to provide better boundary adherence. Second, we proposed a robust similarity measure for comparing regions using both global multi-scale and common border criteria. This measure integrates border information to prevent merging overlapped regions. Third, a merging strategy is designed to control region aggregations through iterations using an adaptive similarity threshold. This strategy ensures that aggregations occur in the order of decreasing similarity. We confirmed the effectiveness of the proposed contributions through comparisons with well-established segmentation approaches using the BSDS500 image dataset. For further research, the proposed superpixels SEM Image segmentation-based region-growing method can be easily extended to semantic segmentation since aggregated superpixels SEM Image segmentations can provide a powerful high-level semantic description.

REFERENCES

1. R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Su¨sstrunk. Slic superpixels SEM Image segmentations compared to state-of-the-art superpixels SEM Image segmentation methods. IEEE *transactions on pattern analysis and machine intelligence*, 34(11):2274–2282, 2012.
2. R. Adams and L. Bischof. Seeded region growing. IEEE *Transactions on pattern analysis and machine intelligence*, 16(6):641–647, 1994.
3. P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik. Contour detection and hierarchical image segmentation. IEEE *transactions on pattern analysis and machine intelligence*, 33(5):898–916, 2011.
4. S. Arora, J. Acharya, A. Verma, and P. K. Panigrahi. Multilevel thresholding for image segmen- tation through a fast statistical recursive algorithm. *Pattern Recognition Letters*, 29(2):119– 125, 2008.
5. A. Baˆazaoui, W. Barhoumi, A. Ahmed, and E. Zagrouba. Semi-automated segmentation of single and multiple tumors in liver ct images using entropy-based fuzzy region growing. IRBM, 2017.
6. M.-H. Chen, J. Wen, Y. Zhu, H.-Y. Xing, and Y. Wang. Multi- level thresholding for pupil location in eye-gaze tracking systerm. In Machine Learning and Cybernetics (ICMLC), 2016 International Conference on, volume 2, pages 1009–1014. IEEE, 2016.
7. G. A. Castillo. A k-means based watershed imaging segmentation algorithm for banana cluster quality inspection. 2016.
8. D. Comaniciu and P. Meer. Mean shift: A robust approach toward feature space analysis.IEEE *Transactions on pattern analysis and machine intelligence*, 24(5):603–619, 2002.
9. P.-H. Conze, V. Noblet, F. Rousseau, F. Heitz, V. de Blasi, R. Memeo, and P. Pessaux. Scale- adaptive supervoxel-based random forests for liver tumor segmentation in dynamic contrast- enhanced CT scans. International Journal of Computer Assisted Radiology and Surgery, 12(2):223–233, 2017.
10. P. Doll´ar and C. L. Zitnick. Structured forests for fast edge detection. In Proceedings of the IEEE International Conference on Computer Vision, pages 1841–1848, 2013].
11. J. Freixenet, X. Mun˜oz, D. Raba, J. Mart´ı, and X. Cuf´ı. Yet another survey on image segmen- tation: Region and boundary information integration. In European Conference on Computer Vision, pages 408–422. Springer, 2002.
12. R. M. Haralick and L. G. Shapiro. Image segmentation techniques. Computer vision, graphics, and image processing, 29(1):100–132, 1985.
13. R. Hettiarachchi and J. F. Peters. Voronoï region-based adaptive unsupervised color image segmentation. Pattern Recognition, 65:119–135, 2017.
14. A. Mehnert and P. Jackway. An improved seeded region growing algorithm. Pattern Recogni- tion Letters, 18(10):1065–1071, 1997.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication