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A Novel Image Segmentation Technique with N-L Means Filter Using Region Merging Strategy

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ABSTRACT

Image segmentation is a branch of digital image processing which emphases on splitting an image into different fragments according to their features. This work proposes a novel image segmentation technique using fast non local (N-L) means filter with region merging approach. Here, a random noise is added to the original image and discrete wavelet transform (DWT) is applied to separate the low and high frequency bands of the digital image. The low frequency component is subjected to a fast N-L means filter and the filtered image is segmented by graph-based segmentation technique. Here, these segmented image regions are merged to reduce the over segmentation patterns. The detailed coefficients of the image component are treated with soft threshold filter to reduce the residual noise. Finally merged image is combined with preserved edge features at wavelet projection resulting in better segmented image. The results are compared with some of the best methods available in literature and are found to be significantly better.

Keywords: Discrete wavelet transform (DWT), fast NL-means filter, graph-based segmentation, boundary based hierarchical region merging, soft-thresholding, peak signal to noise ratio (PSNR).

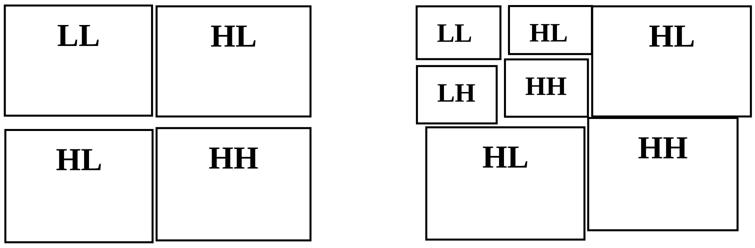
INTRODUCTION

Image segmentation is an essential part in image analysis, which plays an important role in computer-vision medical imaging and remote sensing applications. Various algorithms have been proposed to analyze and extract the hidden features of the image. Basically, image segmentation techniques are broadly classified into different types based on the method involved in extracting the information from the images. Thresholding based, edge based, region based, clustering, ANN based, PDE based, watershed based and hybrid segmentations are used in various fields [1]. The goal of segmentation is to change the representation of an image, so that it becomes more meaningful and easier for analysis. The segmentation techniques are commonly used to reduce the complexity involved in analysis of image features, locating objects and boundaries such as lines, curves and hidden patterns in an image [2-8]. Image segmentation is nothing but partitioning a digital image into its constituent parts, the result of this process helps in image analysis and interpretation. There are many image segmentation techniques have been shown in various studies in the literature. However, there are many challenging concerns affecting performances of these techniques. Therefore, successful image segmentation depends on reliability and accuracy of segmentation method [11], [14], [20- 26].

1.1 Discrete wavelet transforms (DWT)

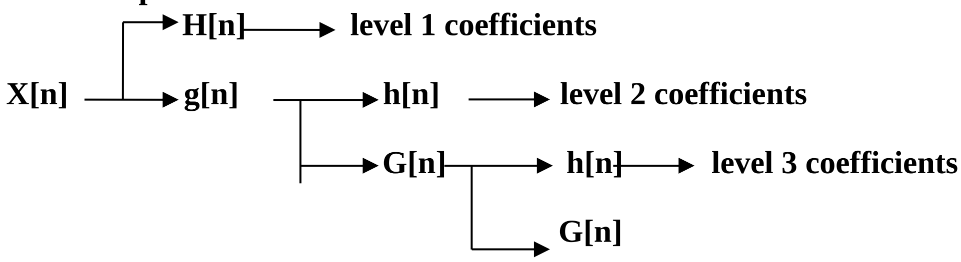
A discrete wavelet transform is used to decompose the digital image into low frequency details and high frequency details of the image [2]. During pre-processing wavelet coefficients are decomposed according to the Mallet's pyramidal representation, which involve L_0, L_1 and L_2

levels and so on [3-4]. Finally, at the projection level, both low frequency and high frequency image details are combined to produce meaning full image features [3-6].



Scale-1 **Scale-2**

Pyramidal representation



1.2 Segmentation and Region merging

A region in an image is a set of associated pixels with similar properties. Regions are important for the analysis of an image because they may resemble to objects in a scene. A region merging strategy is an essential part in image segmentation and it helps to reduce the over segmented patterns. In the past few decades, a variety of methods, such as statistical region merging (SRM), dynamic region merging (DRM), split and merge, similarity based merging, hierarchical merging, boundary based merging etc., have been developed to eliminate the segmentation errors [10-15].Here, image regions can be described in terms of shape, size, color, texture etc., and utilization of these kinds of parameters in region based merging techniques will enhance the efficiency of the method and improve the segmentation patterns [17-20], which are purely based on probabilistic and some logical criteria. In case, to determine the similarity between the two regions depends on pixel mean, variance and gray level, also which is based on Euclidean distance and log–likelihood ratio are well-known statistics for region evaluation. The main goal of region merging operation is to eliminate the false boundaries and spurious regions by merging adjacent regions that belong to the same object [21-29].

Regions produced using thresholding.

$$\boldsymbol{P(R\_i) = true} \qquad (\mathbf{1})$$

Merging adjacent image regions.

$$\boldsymbol{P(R\_i \cup R\_j) = false} \qquad (\mathbf{2})$$

1.3 Soft threshold

A soft threshold is a pre-processing tool, which reduces the residual noise in high frequency details of the image. During visualization Pixels with intensity values below the threshold value are suppressed. In image segmentation, use of soft thresholding filter provides better image smoothing while preserving edge/texture details of the image [2-6]. By filtering image in wavelet domain, shrinks the wavelet coefficients to zero. On other hand the few large wavelet coefficients preserve almost the whole energy of the signal, the shrinkage reduces the noise without distorting the high frequency image features [30-32]. During reconstruction of image, the contamination due to residual

noise is significantly suppressed, while sharp features of the original image get sharper at wavelet projection [36].
Threshold estimation depends on sub-band data, and the threshold value is given by

$$\boldsymbol{T_N} = \frac{\boldsymbol{\beta_{\hat{\sigma}}^2}}{\boldsymbol{\hat{\sigma}_y}} \qquad (3)$$

For each scale $\boldsymbol{\beta}$is computed

$$\boldsymbol{\beta} = \sqrt{\boldsymbol{log\frac{L_k}{J}}} \qquad (4)$$

$\boldsymbol{L_k}$ is length of the sub-band at $\boldsymbol{k_{th}}$ scale, sub-band ***HH1*** is estimates the noise variance $\boldsymbol{\hat{\sigma}^2}$

$$\boldsymbol{\hat{\sigma}^2} = [\frac{\boldsymbol{median}(|\boldsymbol{Y_{ij}}|)}{\boldsymbol{0.6745}}]^2, \boldsymbol{Y_{ij} subbandHH1} \quad (5)$$

σ̂_y Is the standard deviation of the sub-band.

2. Proposed method

This paper introduces a new algorithm to segment an image with the help of wavelets.

In this method, haar wavelet is used to preserve the finer edge details. During pre-processing contamination due to random noise in low frequency image block is suppressed by fast NL-means filter. Here, the presence of residual noise in high frequency image details is reduced by fixing suitable soft thresholding filter [2-5]. The purpose of filtering is to denoise the image while retaining edge/texture details of the image [9-11].
The discrete wavelet transform signal ***x(n)*** is defined based on approximation coefficients $\boldsymbol{w\_\varphi\ [j\_0, k]}$ and detailed coefficients $\boldsymbol{w\_\Psi\ [j, k]}$.

$$\boldsymbol{W_{\emptyset}[j_{0,}k]} = \frac{\boldsymbol{1}}{\sqrt{\boldsymbol{M}}}\sum_{\boldsymbol{n}} \boldsymbol{x\ [n]\emptyset_{j0,k}[n]} \qquad (6)$$

$$\boldsymbol{W_{\Psi}[j,k]} = \frac{\boldsymbol{1}}{\sqrt{\boldsymbol{M}}}\sum_{\boldsymbol{n}} \boldsymbol{x[n]\ \Psi_{j,k}[n] for j} \geq \boldsymbol{j_0} \qquad (7)$$

For IDWT,

$$\boldsymbol{x[n]} = \frac{\boldsymbol{1}}{\sqrt{\boldsymbol{M}}}\sum_{\boldsymbol{k}} \boldsymbol{W_{\varphi}\ [j_{0,}k]\varphi_{j_{0},k}[n]} + \frac{\boldsymbol{1}}{\sqrt{\boldsymbol{M}}}\sum_{\boldsymbol{j=j_0}}^{\boldsymbol{J}} \sum_{\boldsymbol{k}} \boldsymbol{W_{\varphi}\ [j,k]\ \varphi_{j,k}} \qquad (8)$$

Where, **n** = ***0, 1, 2, M–1,*** **j** ***= 0, 1, 2,*** **J–*1,*** **k** = ***0, 1, 2,*** $\boldsymbol{2^j}$***–1,*** and ***M*** is number of samples. This number is selected to be $\boldsymbol{M = 2^J}$, where ***J*** indicates the number of transform levels, where, ***φ[*n*]*** is the scaling function and ***ψ[*n*]*** is the wavelet function.
The low frequency component of the decomposed image is subjected to fast NL-means filter which reduces noise information drastically without losing approximation coefficients of the image. Here, image is decomposed up to scale-2 with different standard test images [33-34].
In the theoretical formulation of the fast NL-means filter, the restored intensity of the pixel ***i, NL (v) (i),*** is a weighted average of all pixel intensities in the image ***I***.

$$\boldsymbol{NL(v)(i)} = \sum_{\boldsymbol{j \in i}} \boldsymbol{w(i,j)v(j)} \qquad (9)$$

Where *v* is the intensity function and ***v(j)*** is the intensity at pixel ***j*** and ***w(i,j)*** is the weight assigned to ***v(j)*** in the restoration pixel ***i***. The original definition of the fast NL-means algorithm considers that each pixel can be linked to all the others, but practically the number of pixels taken into account in the weighted average can be restricted in a neighborhood. The similarity between ***i*** and ***j*** depends on the similarity of their local neighborhoods and averaged Euclidean distance. The common problem that arises in this method is the computational burden with a neighborhood classification. The aim here is to reduce the number of pixels taken into account in the weighted average and to avoid repetitive calculations of same neighborhood.

$$w(i,j)=\begin{cases}\frac{1}{z(i)}e^{-\frac{\left\|v(N_i)-v(N_j)\right\|_{2,a}^{2}}{h^2}} & if\mu_1<\frac{\overline{v(N_i)}}{\overline{v(N_j)}}<\mu^2 and \sigma_2^1<\frac{var(v(N_i))}{var(v(N_j))}<\sigma_2^2 \\ 0 & othrewise.\end{cases} \quad (10)$$

Where, $z(i)$ is the normalization constant with $z(i)=\sum\_j ⟦w(i,j)\ and\ h⟧$ acts as a filtering parameter.

$v(N\_i)$ and $v(N\_j)$ are the similarities between the neighborhood intensities.

Distance between $v(N\_i)$ and $v(N\_j)$ is a classical norm$|(|-|)|_a$, convolved with a Gaussian kernel of standard deviation.

The pre-processed image is further segmented by Felzenszwalb graph-based segmentation technique. Here, even though, over segmentation patterns were found, the necessary details of the image are more meaningful compare to traditional morphology-based watershed segmentation. Therefore, the image is subjected to boundary-based region merging to reduce the over segmentation patterns. In case of watershed segmentation region merging would reduce the over segmentation but regions which are merged will not have a perfect boundary, leading to an over region merging [3], [5], [10], [13]. In proposed work after region merging process, representation of image is more meaningful and provides better image understanding and helps in recognizing the hidden patterns [17], [19], [22].

Felzenszwalb is an efficient graph-based image segmentation technique, in which, each pixel from the node matches a node in the graph, forming a connection between the nodes representing the neighbors. In this method, edges are taken from the graph and pixel is represented as a node. The weights for every edge represent the measure of the variation among the pixels. This technique is useful to recognize the hidden patterns of the image [25], [26], and [35].

Regions are allowed to be merge, if they are separated mostly by 'weak' edges. Neighboring pixels with intensity difference at most T_0 will be merged together to form the initial regions. Neighboring pixels with intensity difference at most T_1 will be considered as 'weak edge', which, encourage melting. Regions are merged if their boundary contains at least T_2 ***min*** (I_1,I_2) weak edges. Regions are merged if their common boundary contains at least T_3, I. In the proposed work, regions with the lowest edge weights are successively merged until there is no edge with weight less than threshold [8], [10], and [12].

The number of pixels associated to each region adjacency graph (RAG) are represented as node, which indicates the size of initial over segmented regions and they must be same as the reference node. RAG-based segmentation approach is hierarchical and the number of final regions are controlled manually according to the segmentation requirements [13-20].

In graph partition problem, objects which are extracted not necessarily connected and the set of edge weights reflects the similarity between each pair of related regions or nodes vi and vj. These connected components may be adjacent or may not be, but if adjacency is not done, these components are closer than a determined distance threshold rx.

The weights $wij \in W$ are computed by the conditional function given by

$$if(|x_i-x_j|<r_x) then\ w_{ij} e^{\frac{-c_{ij}(I_i-I_j)^2}{\sigma_I^2}} . e^{\frac{-c_{ij}(x_i-x_j)^2}{\sigma_x^2}} else w_{ij}=0 \quad (11)$$

Where, rx, σx and σI are experimental values.

I_i is the mean intensity of region i, and x_i is the spatial centre-of-gravity of that region.

Finally, the factor C_{ij} takes into account the cardinality of the regions i and j.

$$c_{ij} = \frac{||E_i||.||E_j||}{||E_i|| + ||E_j||} \qquad (12)$$

where, $||E_i||$, $||E_j||$ are number of pixels in regions vi and vj. Non-significant weighted edges, according to the defined similarity criteria, are removed from the image graph [21-26].

However, the presence of residual noise in high frequency image details is suppressed by Visushrink soft thresholding filter which is the most effective and efficient wavelet-based thresholding technique used for the purpose of denoising. It follows the global thresholding scheme, where a single value of threshold applied globally to all the high frequency wavelet coefficients. It provides better image smoothing during pre-processing level and results are very smooth with a better visual quality during wavelet projection level [30-36].

The Visushrink, is defined as

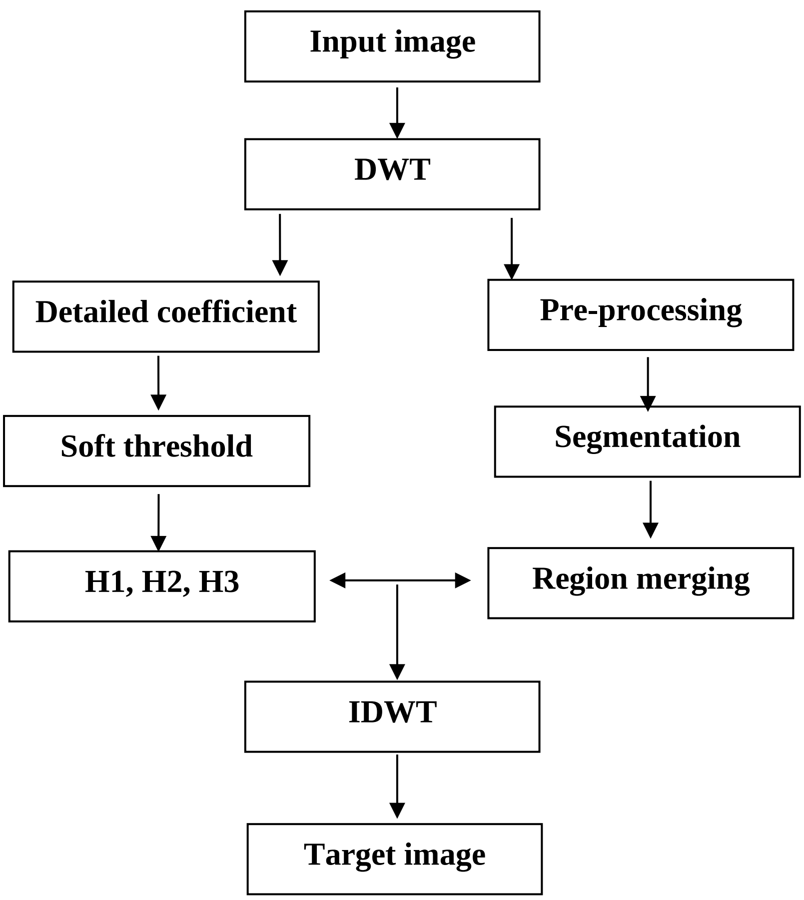
$$\sigma\sqrt{2logM} = T \qquad (13)$$

Where, σ^2 is the noise variance and M is the image length. The noise variance σ^2 is estimated from the high frequency component, by the median estimator shown in equation.

$$\sigma = \frac{median\{|W_k|: k = 1, 2, \dots n\}}{0.06745} \qquad (14)$$

W_k = Detail coefficients at the finest level

2.1 Algorithm flow



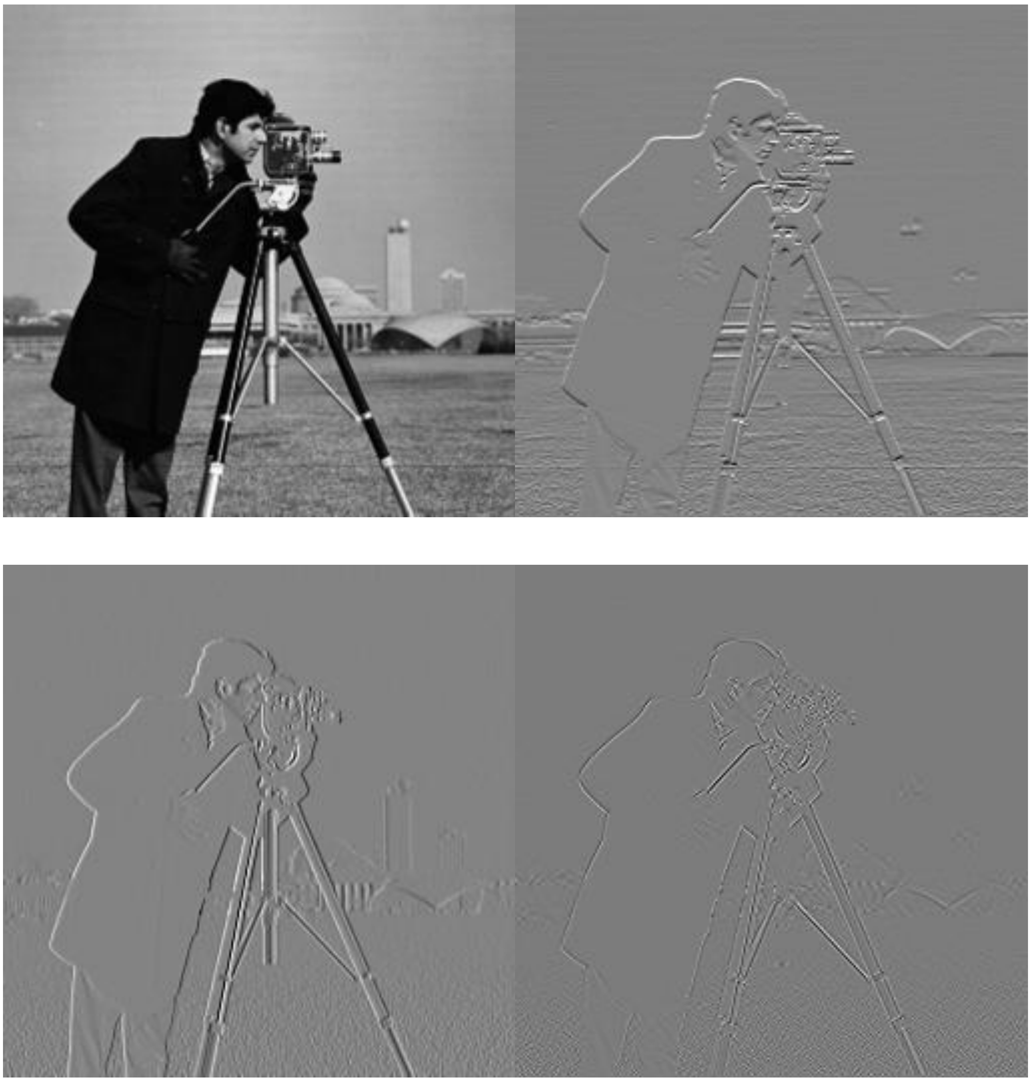
2.2 Algorithm steps:

Input: standard and Satellite image are extracted from Berkley dataset, to be segmented

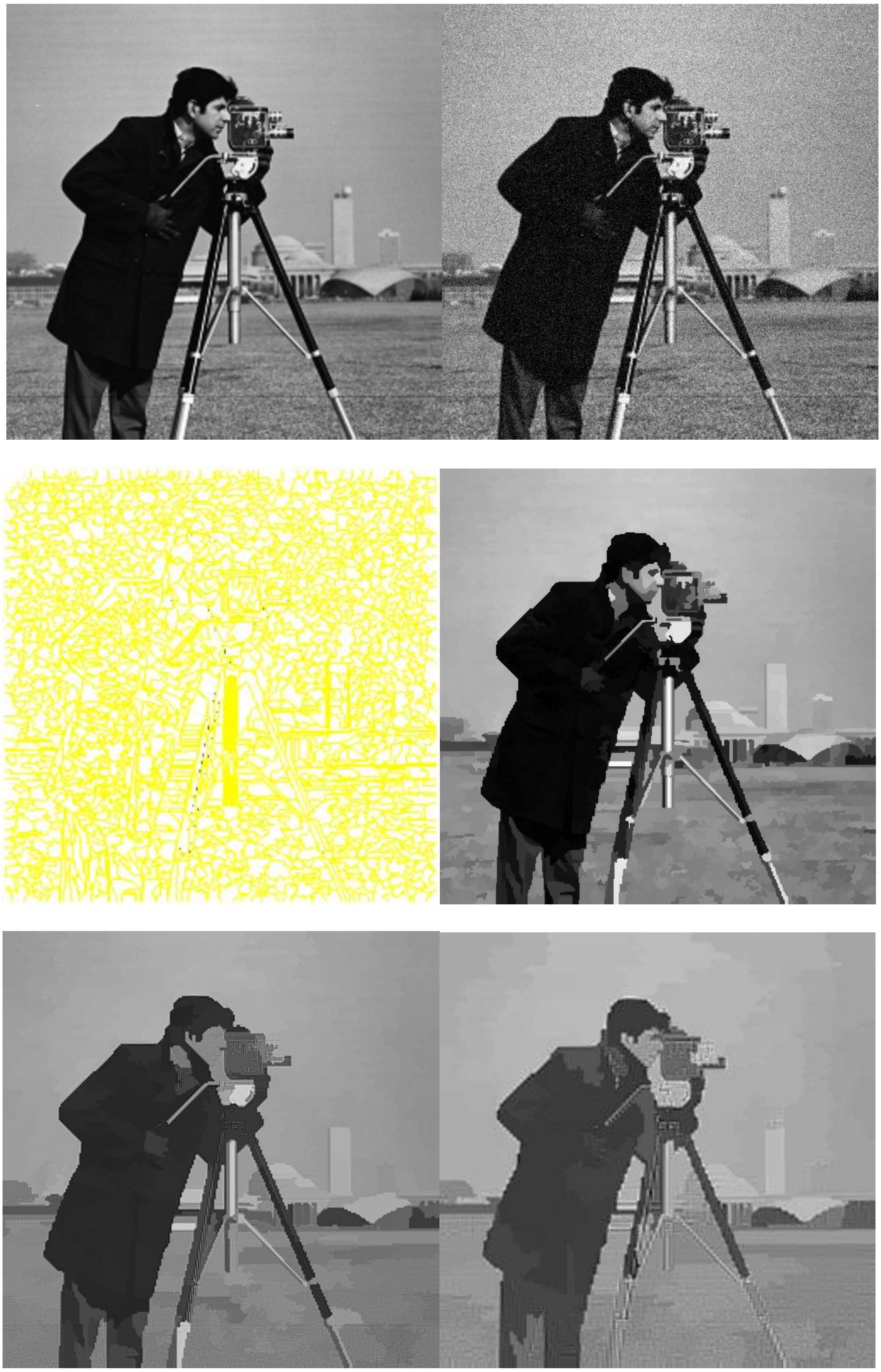
Output: Segmented image

- A discrete wavelet transform is applied to an input image to obtain the wavelet decomposed image.
- LL sub-band is denoised by using fast NL-means filter.
- Felzenszwab segmentation technique is applied to extract the required features from denoised image.
- Boundary based hierarchical region merging is used to reduce the over segmentation.
- Soft thresholding is applied to detailed coefficients.
- Combination of wavelet coefficients are projected into full original form by inverse wavelet transform.

RESULTS AND DISCUSSIONS

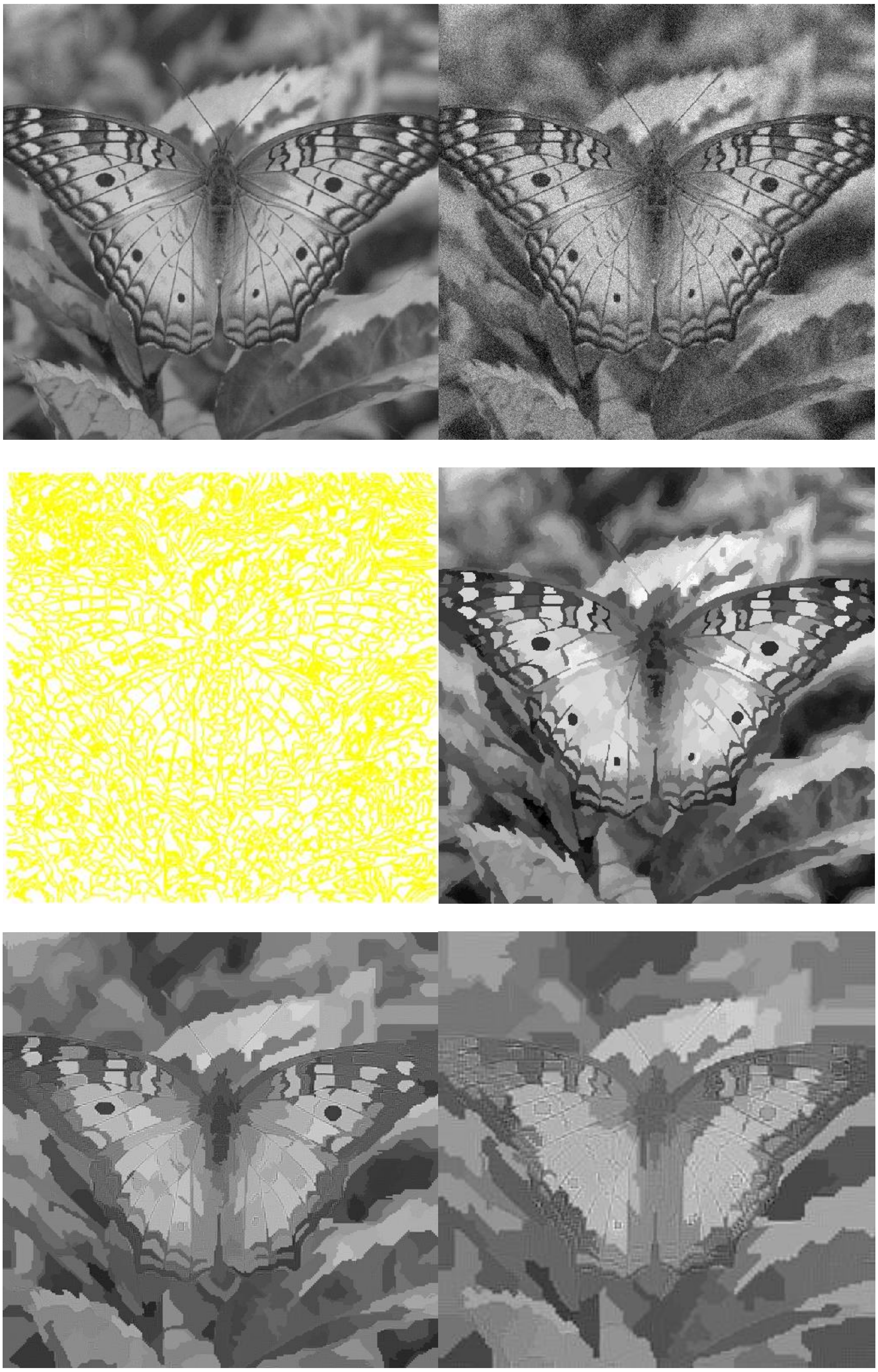


A) Approximation and detailed coefficients of first level decomposition

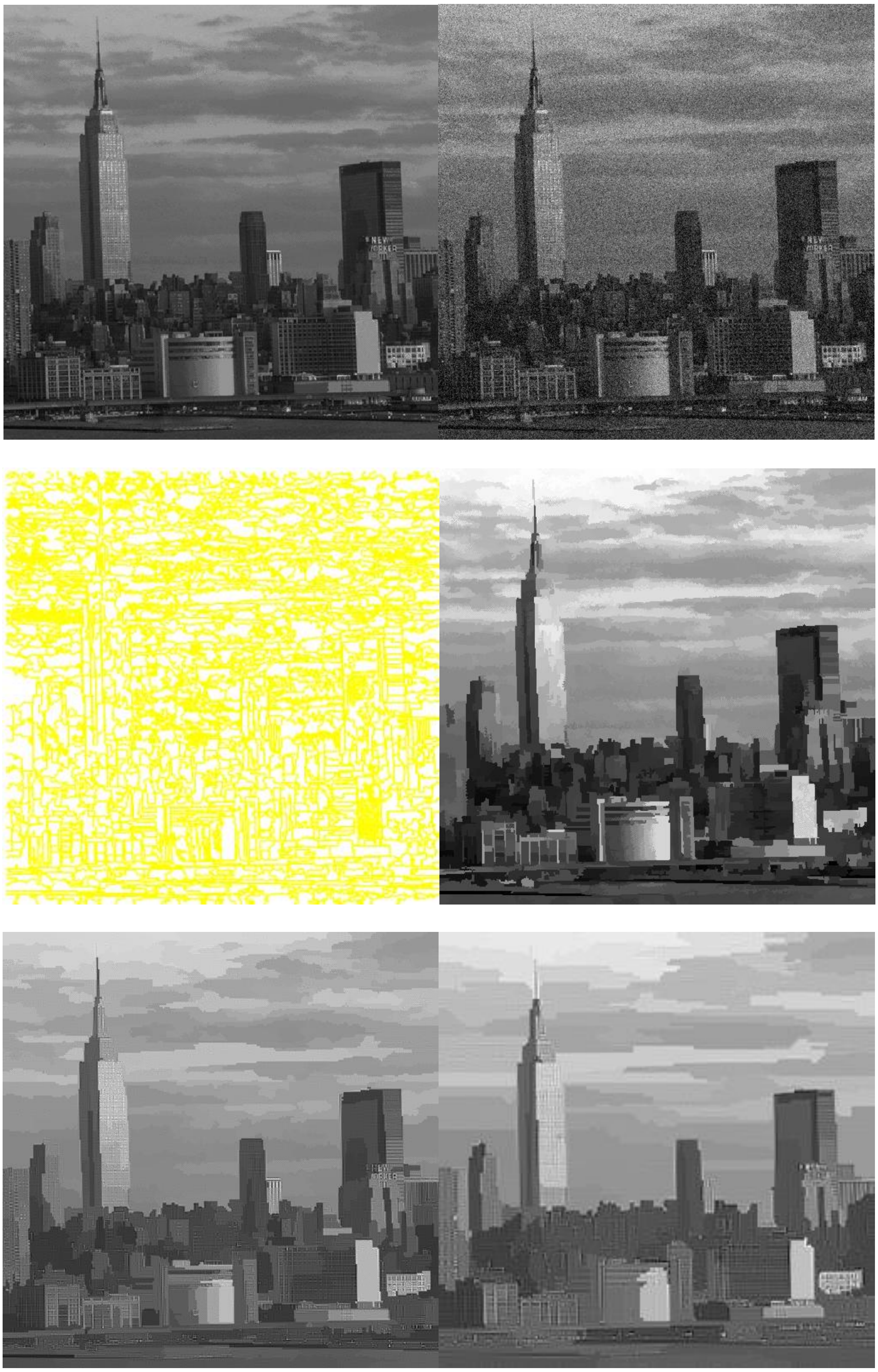


A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$.

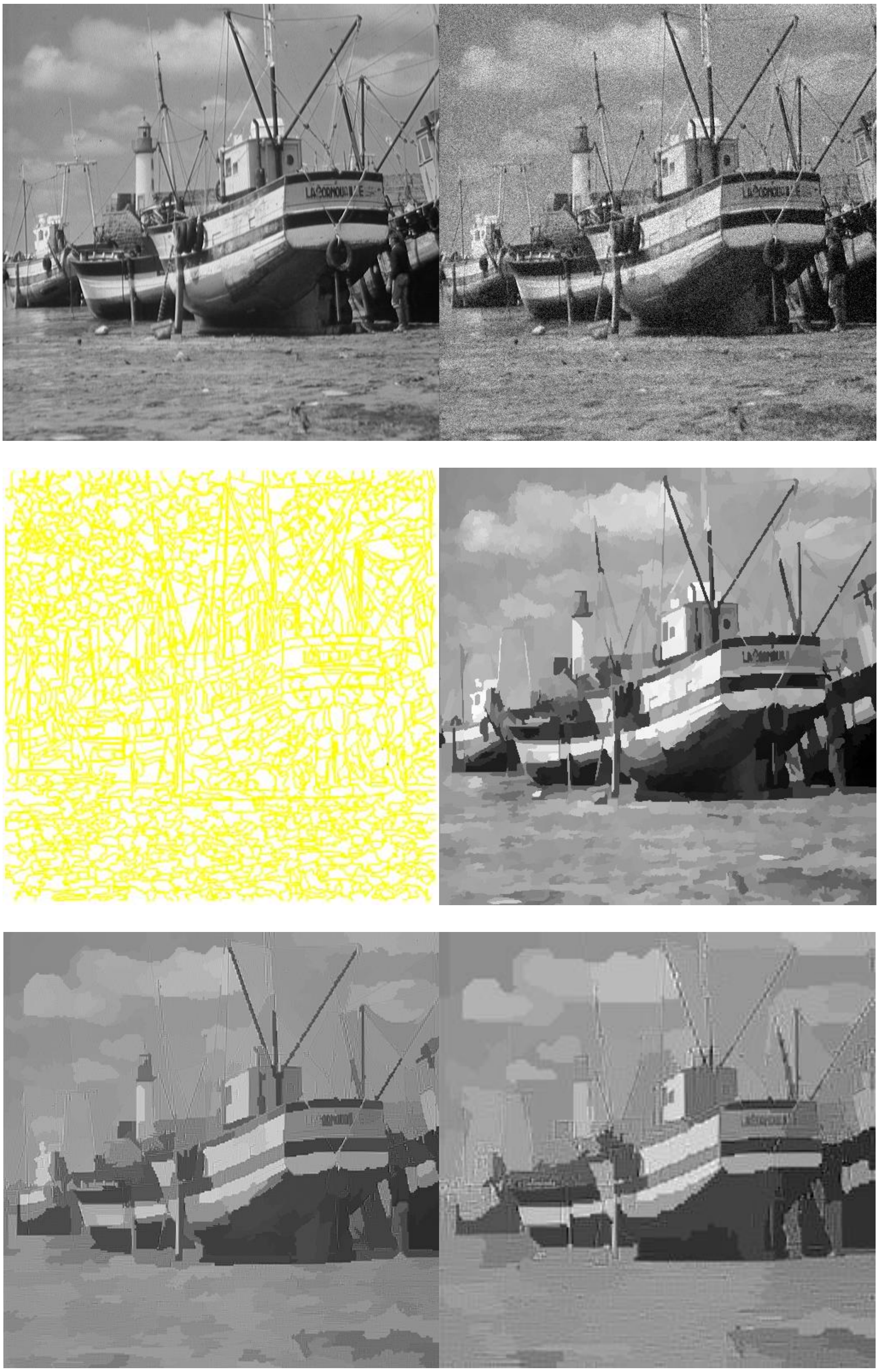
A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$



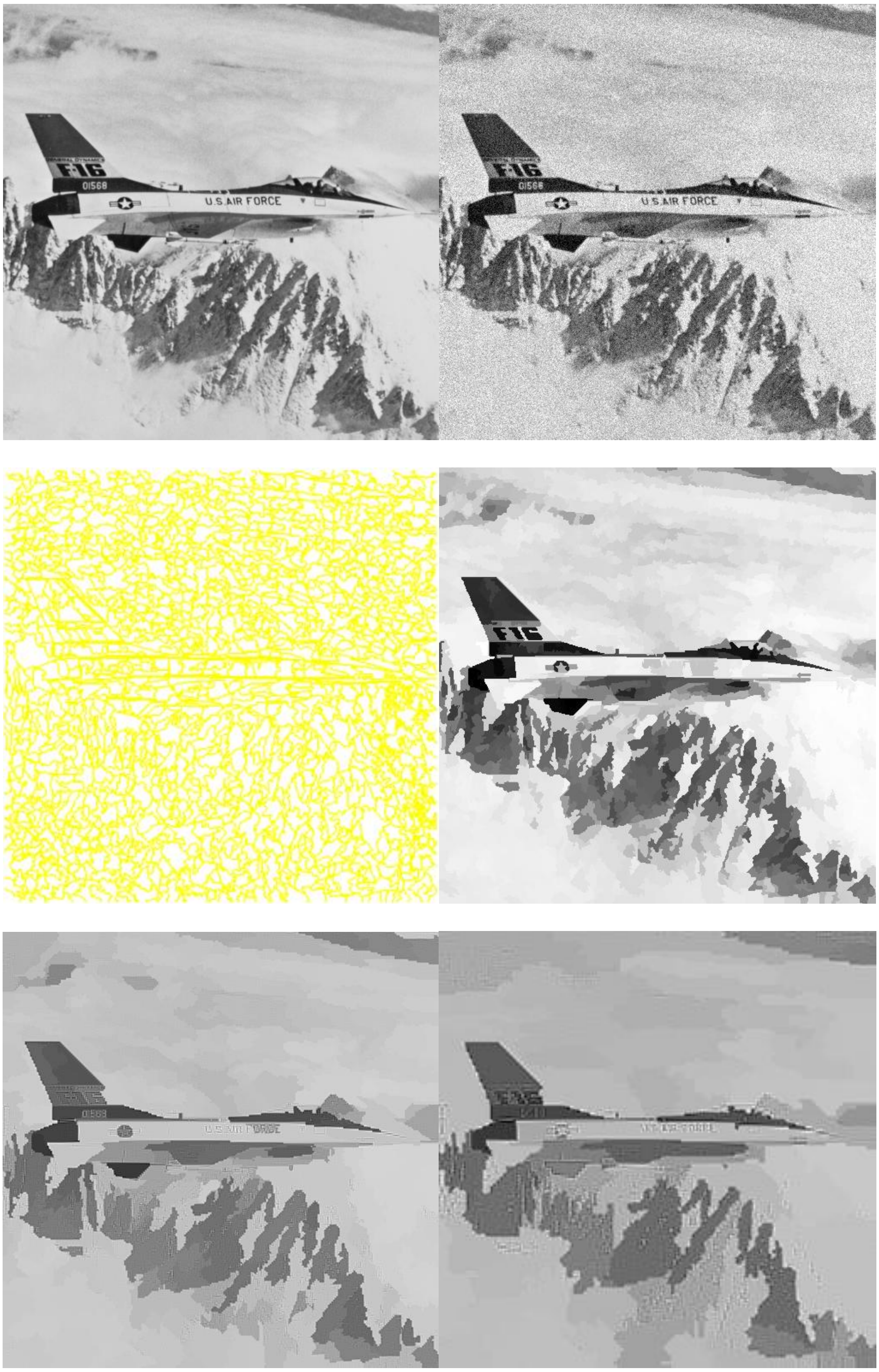
A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$.



A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$.

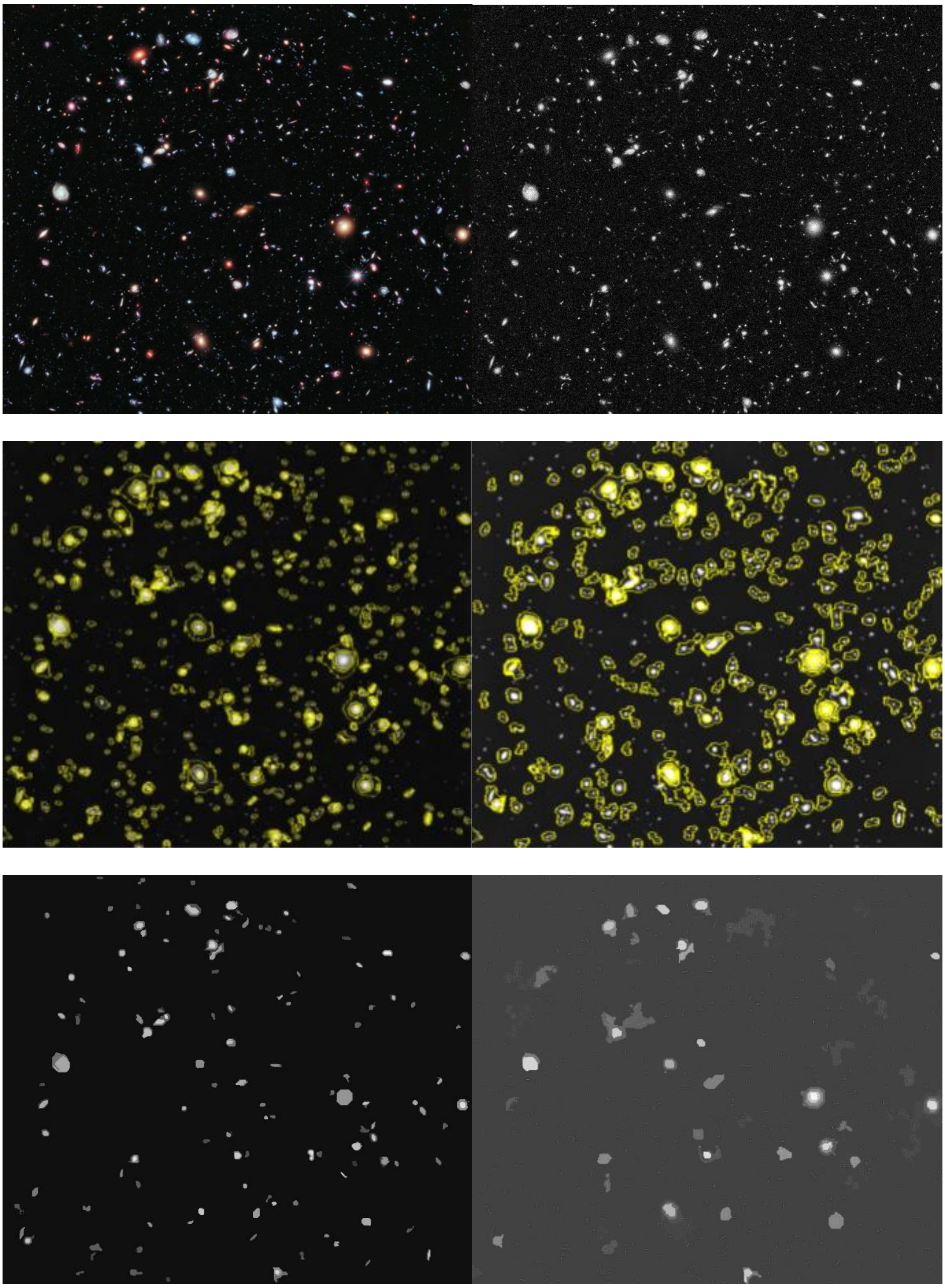


A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$.

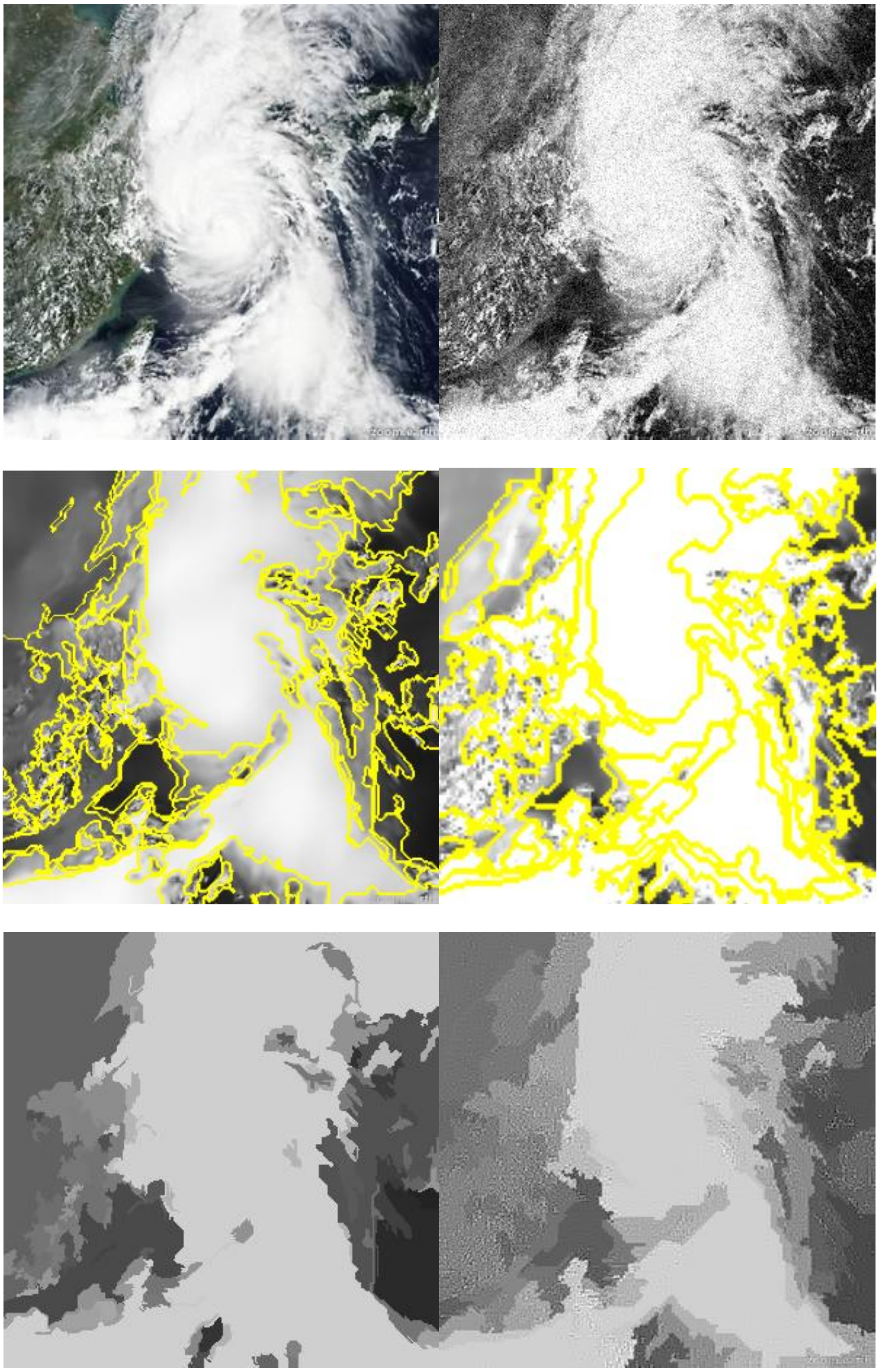


A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$.

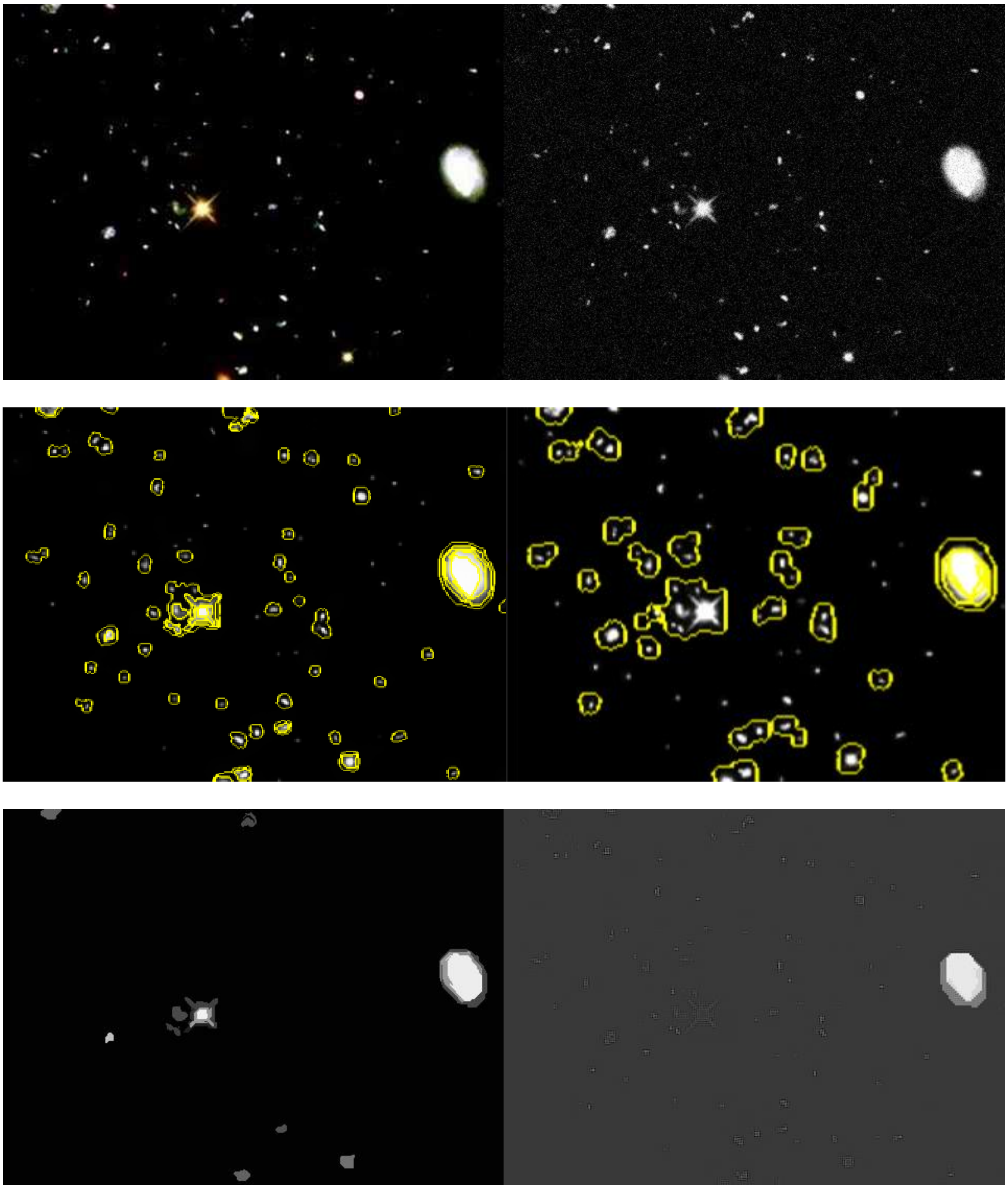
A)original image, B)noisy image, C)segmented image, D)region merging level$_0$, level$_1$, level$_2$.



A)original image, B)noisy grayscale image, D)segmented image level$_0$,level$_1$,D)region merging level$_0$, level$_1$.



A)original image, B)noisy grayscale image, D)segmented image level$_0$,level$_1$, D)region merging level$_0$, level$_1$.



A)original image, B)noisy grayscale image, D)segmented image $level_0$,$level_1$, D)region merging $level_0$, $level_1$.

Performance matrix

$$psnr = 10.log_{10}\left(\frac{max^2}{mse}\right) \qquad (15)$$

RESULT

Test image	scale	Number of segments	Number of regions	Estimated noise standard deviation	Time (s)
Cameraman	L_0	1394	181	0.0766	7.17
	L_1	352	153	0.0762	3.06
	L_2	94	77	0.0767	2.25
Lena	L_0	1281	196	0.0806	7.00
	L_1	322	182	0.0808	2.95
	L_2	87	73	0.0808	2.18
Butterfly	L_0	1345	170	0.0850	7.10
	L_1	345	187	0.0854	3.09
	L_2	93	72	0.0850	2.24
Building	L_0	1311	146	0.0842	6.89
	L_1	354	183	0.0843	2.97
	L_2	100	82	0.0835	2.18
Fishing Boat	L_0	1253	201	0.0821	7.07
	L_1	311	163	0.0821	3.01
	L_2	96	80	0.0823	2.24
Air-plane	L_0	1274	173	0.0823	6.63
	L_1	303	132	0.0827	2.87
	L_2	83	72	0.0823	2.27
Barbara	L_0	1224	200	0.0863	6.86
	L_1	319	183	0.0858	2.94
	L_2	97	80	0.0862	2.33

3.1 Table shows the standard image segmentation score:

Test image	scale	Number of segments	Number of regions	Estimated noise standard deviation	PSNR (dB)	Time (s)
Satellite image.1	L_0	554	174	0.0660	23.14	19.3
	L_1	238	73	0.0660	22.59	6.50
Satellite image.2	L_0	162	116	0.0870	15.00	2.99
	L_1	90	78	0.0870	19.33	2.38
Satellite image.3	L_0	68	18	0.0420	25.66	4.13
	L_1	32	4	0.0430	23.76	2.47

3.2 Satellite image segmentation score:

CONCLUSION

This work proposes a new segmentation technique by using fast NL-means filter with Felzenszwalb graph-based segmentation. The proposed algorithm gives more robust segmentation results as compared to traditional watershed segmentation technique. Consistency of the segmentation technique reveals the image features with reduced complexity. This method can be localized for different types of images like remote images for object detection and also used for various standard images. Comparison of number of segments, regions, and the peak signal to noise ratio (PSNR) values of proposed method with watershed-based method indicates the goodness of the method. Also, the image denoising and segmentation results get better with increase in wavelet decomposition levels. The reduction in over segmentation by boundary-based region merging technique, leads to more meaning full image features, as compared to watershed-based region merging techniques. The soft thresholding provides a smoothing effect at the image projection into full resolution. The proposed algorithm produces consistency in segmentation, region merging and has better computation time.

Declaration by Authors

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REFERENCES

1. N. R. Pal, S. K. Pal. A review on image segmentation techniques, Pattern Recognition, vol. 26, no. 9, pp. 1277-1294, 1993. https://doi.org/10.1016/0031-3203(93)90135-.
2. Jung, C. R. (2007). Combining wavelets and watersheds for robust multiscale image segmentation. Image and Vision Computing,

25(1), 24 33. doi: 10.1016/j. imavis.2006.01.002.
3. Jung, C. R. (n.d.). Multiscale image segmentation using wavelets and watersheds. 16th Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI 2003). doi:10.1109/sibgra.2003.1241020.
4. Yu-hua Chai, Li-qun Gao, Shun Lu, & Lei Tian. Wavelet-based Watershed for Image Segmentation Algorithm. World Congress on Intelligent Control and Automation. 2006, 6th doi:10.1109/wcica.2006.1713863.
5. Haihua Liu, Zhouhui Chen, Xinhao Chen, & Yaguang Chen. Multiresolution Medical Image Segmentation Based on Wavelet Transform. IEEE Engineering in Medicine and Biology 27th Annual Conference. 2005, doi:10.1109/iembs.2005.1617212.
6. Ruikar, S., & Doye, D. D. (2010). Image denoising using wavelet transform. 2010 International Conference on Mechanical and Electrical Technology. doi:10.1109/icmet.2010.5598411.
7. Hu, C., Jiang, L.-J., & Bo, J. Wavelet transform and morphology image segmentation algorism for blood cell. 4th IEEE Conference on Industrial Electronics and Applications. 2009, doi:10.1109/iciea.2009.5138265.
8. Garzelli, A., Benelli, G., Barni, M., & Magini, C. Image and Signal Processing for Remote Sensing VI. doi:10.1117/12.413884.
9. Kim, J.-B., & Kim, H.-J. Multiresolution-based watersheds for efficient image segmentation. Pattern Recognition Letters, 24(1-3), 473–488. doi:10.1016/s0167-8655(02)00270-2.
10. Haris, K., Efstratiadis, S. N., Maglaveras, N., & Katsaggelos, A. K. Hybrid image segmentation using watersheds and fast region merging. IEEE Transactions on Image Processing, 7(12), 1684–1699. doi:10.1109/83.730380.
11. Ijitona, T. B., Ren, J., & Hwang, P. B. (2014). SAR Sea Ice Image Segmentation Using Watershed with Intensity-Based Region Merging. IEEE International Conference on Computer and Information Technology. 2014, doi:10.1109/cit.2014.19.
12. Ning, J., Zhang, L., Zhang, D., & Wu, C. Interactive image segmentation by maximal similarity-based region merging. Pattern Recognition, (2010), 43(2), 445–456. doi: 10.1016/j.patcog.2009.03.004.
13. Angelina., S., Suresh, L. P., & Veni, S. H. K. Image segmentation based on genetic algorithm for region growth and region merging. International Conference on Computing, Electronics and Electrical Technologies (ICCEET). 2012, doi:10.1109/icceet. 2012.6203833.
14. Bo Peng, Lei Zhang, & Zhang, D. Automatic Image Segmentation by Dynamic Region Merging. IEEE Transactions on Image Processing, 20(12), 3592–3605. doi:10.1109/tip.2011.2157512.
15. Dhanachandra, N., & Chanu, Y. J. A New Image Segmentation Method Using Clustering and Region Merging Techniques. Applications of Artificial Intelligence Techniques in Engineering, 603–614. doi:10.1007/978-981-13-1819-1_57.
16. Ko, B. C., Gim, J.-W., & Nam, J.-Y. Automatic white blood cell segmentation using stepwise merging rules and gradient vector flow snake. Micron, 42(7), 695–705. doi: 10.1016/j.micron.2011.03.009.
17. Sun, H., Yang, J., & Ren, M. A fast watershed algorithm based on chain code and its application in image segmentation. Pattern Recognition Letters, 26(9), 1266–1274. doi: 10.1016/j.patrec.2004.11.007.
18. Garcia, C., & Tziritas, G. Face detection using quantized skin color regions merging and wavelet packet analysis. IEEE Transactions on Multimedia, 1(3), 264–277. doi:10.1109/6046.784465.
19. Wang, H., Shen, Z., Zhang, Z., Xu, Z., Li, S., Jiao, S., & Lei, Y. Improvement of Region-Merging Image Segmentation Accuracy Using Multiple Merging Criteria. Remote Sensing, 13(14), 2782. doi:10.3390/rs13142782.
20. Basavaprasad, B., & Hegadi, R. S. Automatic Multi-Stage Image Segmentation Using Normalized Cut in Gradient Image. Advances in Computational Sciences and Technology, 10(1), 37–51. ISSN 0973-6107.
21. Nock, R., & Nielsen, F. Statistical Region Merging. IEEE Transactions on Pattern Analysis and Machine Intelligence, 26(11), 1. doi:10.1109/TPAMI.2004.91.
22. Swaroopa H Narayan, Basavaraj N Jagadale, Omar Abdullah Murshed Farhan Alnaggar, A Novel Image Denoising and Segmentation Using Machine Learning with SRM Strategy, Indian Journal of Science and Technology, Year: 2022, Volume: 15, Issue:

17, Pages: 778-789, doi: 10.17485/IJST/v15i17.2203.
23. Shih, H.-C., & Liu, E.-R. New quartile-based region merging algorithm for unsupervised image segmentation using color-alone feature. Information Sciences, (2016) 342, 24–36. doi: 10.1016/j.ins.2015.12.030.
24. Mgaga, S. S., Khanyile, N. P., & Tapamo, J.-R. A Review of Wavelet Transform based Techniques for Denoising Latent Fingerprint Images. 2019 Open Innovations (OI). doi:10.1109/oi.2019.8908252.
25. Coupé, P., Yger, P., & Barillot, C. Fast Non-Local Means Denoising for 3D MR Images. Lecture Notes in Computer Science, 33–40. doi:10.1007/11866763_5.
26. Wiest-Daesslé, N., Prima, S., Coupé, P., Morrissey, S. P., & Barillot, C. Rician Noise Removal by Non-Local Means Filtering for Low Signal-to-Noise Ratio MRI: Applications to DT-MRI. Lecture Notes in Computer Science, (2008), 171–179. doi:10.1007/978-3-540-85990-.
27. Felzenszwalb, P. F., & Huttenlocher, D. P. Efficient Graph-Based Image Segmentation. International Journal of Computer Vision, 2004, 59(2), 167–181. doi:10.1023/b: visi.0000022288.197.

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