

A NEW APPROACH OF SEGMENTATION IMAGES BASED ON WAVELET TRANSFORM

Abdelghani Rouini ^{1,2}, Messaouda Larbi ^{2,3}

¹Department of Science and Technology, Ziane Achour University of Djelfa, Algeria

²Applied automation and industrial diagnostic Laboratory, Ziane Achour University of Djelfa, Algeria

³Department of Computer Science, Ziane Achour University of Djelfa, Algeria

Abstract

In this work, we present an approach to region-contour cooperative segmentation that has gained significant interest in recent years. It involves cooperation between region-based segmentation and contour-based segmentation. It exploits the advantages of both segmentation types to achieve a more accurate and faithful segmentation result than what can be obtained using a single technique. Wavelets have been applied to transform the image and reconstruct the model at a higher resolution. Then, the segmentation is performed using Active Contour (Region Scalable Fitting (RSF)). A comparison with the result obtained from active contour segmentation demonstrates the advantages of adopting such cooperation.

Keywords: Image segmentation. Region-contour cooperation. Wavelets. Active Contour.

1. Introduction

Medical imaging encompasses all the techniques used in medicine for the diagnosis and treatment of numerous pathologies. It has revolutionized medicine by providing immediate and reliable access to information that was previously "invisible" to clinical diagnosis, such as anatomical characteristics and even certain aspects of organ metabolism (functional imaging) [1]. Imaging allows for the exploration of living organisms and has become a valuable tool for the implementation of personalized medicine.

It provides complementary information to the patient's biological data, enabling earlier diagnosis and more targeted and tailored treatment. Methods for processing and analyzing medical images are fundamental and indispensable. [2]. This field is an integral part of medical imaging, and one of the objectives of image processing is to separate the image into components or regions that are meaningful for a specific analysis.

This is referred to as image segmentation. For example, it can involve counting and measuring cells of a certain type in a blood sample. It can also involve recognizing a tumor in a brain image in order to precisely measure its position and dimensions or delimit the unaffected white and gray matter of the brain [3-5]. Given its importance, various segmentation approaches have been proposed.

Wavelet transformation has emerged as a powerful tool for solving problems in different application domains [6-9], such as local tomography, image segmentation and enhancement, and texture description. Here, we focus on the contribution of wavelets to the (local and global) reconstruction of anatomical structures: automatic segmentation using active contour.

Our main objective is to study and implement effective segmentation methods using a cooperative approach of wavelet decomposition and active contour techniques.

2. Image Segmentation using new approach of Wavelets

In these days signals (images) are processed in transform domain. Since this transform domain is purely mathematics, we will focus more on its use in Digital Image Processing and we will try to minimize math's part.

Till now, all the domains in which we have analyzed a signal, we analyze it with respect to time. But in transform domain we don't analyze signal with respect to time, but with respect of frequency.

The wavelet transform has been widely employed in signal processing application, particularly in image processing research. It has been used extensively in Multi-Resolution Analysis (MRA) for image processing. [10]

Image segmentation has a very important role in image analysis. for image analysis and features extraction, model-based segmentation algorithm will be more efficient compared to non-parametric methods and its height recommended to make this process fast and simple as possible as can, An important issue in the segmentation process is to locate the edges. With wavelet transform, we can analyze a portion of a signal with different scales. We can distinguish the noise and actual corner more precisely. That is why we proposed new method Image Segmentation using Wavelets. [11-13].

The approximation band of image Discrete Wavelet Transform is used for the segmentation process which contains significant information of the input image.

The wavelet transform has many advantages in the field of signal processing and image processing. The wavelet analysis is no longer limited to the image as it appears, but allows the study of objects in the image at different scales, it improves segmentation of an image it can also extract important information (texture, contours, etc.) contained in an image and also reduce the noise in the image.

Principle of Segmentation using Wavelets .a

As we had mention above that the “Automatic Image Segmentation using Wavelets” is more efficient compared to the classic methods and much faster and simpler. Our proposal is similar to Knoll's [14]. In terms of strategy, it consists of a coarse-to-fine adjustment. However, our method avoids the comparison between a reference model and a deformed model. Additionally, our method is directly extendable to the 3D case. Here we will talk about the Principe of our method, the principle is shown in the following steps:

1. Introduce the source image that we want to process.
2. We perform a pretreatment with a low-pass filter (Gaussian for example) to reduce noise of high frequency.
3. Multi resolution decomposition of images using a wavelet basis: Applies the decomposition on the pretreated image obtained from the steps above using the discrete wavelet transform (DWT). The used conjugate mirror filters are Daubechies filters (length 8 with nearly linear phase). At each level j , the image a_j is decomposed into four sub-images: the approximation a_{j+1} and the three detail images. Only the approximation images will be used to guide the contour at different levels j .
4. Reconstruction of the deformed model at a higher resolution.
5. Adjustment of the model to the image using an active contour method: At level j , the contour j is adjusted using an active contour technique [15] on the approximation image a_j . This adjustment will be performed at each resolution level in a coarse-to-fine strategy. The choice of the deformation technique is somewhat arbitrary here. Other approaches could be considered.
6. We perform a post-treatment

Algorithm of Segmentation using new approach Wavelets .b

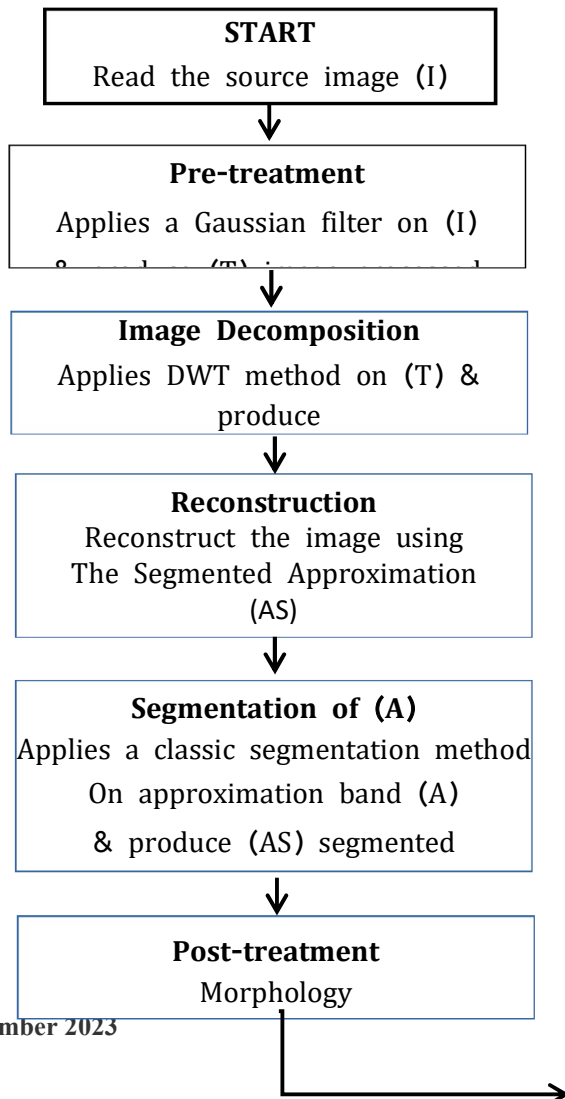


Image Result (R)

c. Segmentation evaluation

Having evaluation methods for segmentation results is necessary:

- For researchers to compare a new algorithm with existing ones.
- For users to choose an algorithm and adjust its parameters based on the problem to be solved.

When a ground truth is available, segmentation evaluation is performed using criteria that compare each segmentation with the reference image. This allows for the ordering of segmentations. In the absence of ground truth, absolute quantitative criteria or coherence calculations between different segmentation results must be employed. In our work, we used the criterion of missegmented pixel position:

Dice Criterion

The Dice coefficient (DICE), also called the overlap index, is the most used metric in validating medical volume segmentations. In addition to the direct comparison between automatic and ground truth segmentations, it is common to use the DICE to measure reproducibility (repeatability). Zou et al. [16] used the DICE as a measure of the reproducibility as a statistical validation of manual annotation where segmented S repeatedly annotated the same MRI image, then the pair-wise overlap of the repeated segmentations is calculated using the DICE, which is defined by:

$$Dice = \frac{2|S_g^1 \cap S_t^1|}{|S_g^1| + |S_t^1|} = \frac{2TP}{2TP + FP + FN} \quad (1)$$

Jaccard

The Jaccard index (JAC) [17] between two sets is defined as the intersection between them divided by their union, that is:

$$JAC = \frac{|S_g^1 \cap S_t^1|}{|S_g^1 \cup S_t^1|} = \frac{TP}{TP + FP + FN} \quad (2)$$

Accuracy

Measures how well a binary segmentation method correctly identifies or excludes a condition [16]:

$$accuracy = \frac{TP + TN}{FP + FN + TP + TN} \quad (3)$$

Yasnoff et al.'s measure

Simply counting the number of missegmented pixels is insufficient; it is also necessary to consider the position of these pixels, for example, measuring the distance between a missegmented pixel and the region to which it belongs in the reference image. The measure by Yasnoff et al. is expressed as follows:

$$\frac{100}{A} * \sqrt{\sum_s d^2(s)} \quad (4)$$

3. Results and Discussions

In this part we will present a small test of the results obtained from our application and we will make a comparison between the results of the wavelet based our method and the results obtained from the classic method, we had chosen to evaluate the results using similarity measurements and a visual comparison basing our work on the medical images since this last one considered as the most important images which needs a good segmentation to get a good diagnostic.

Experimental results

a. The choice of the wavelet used

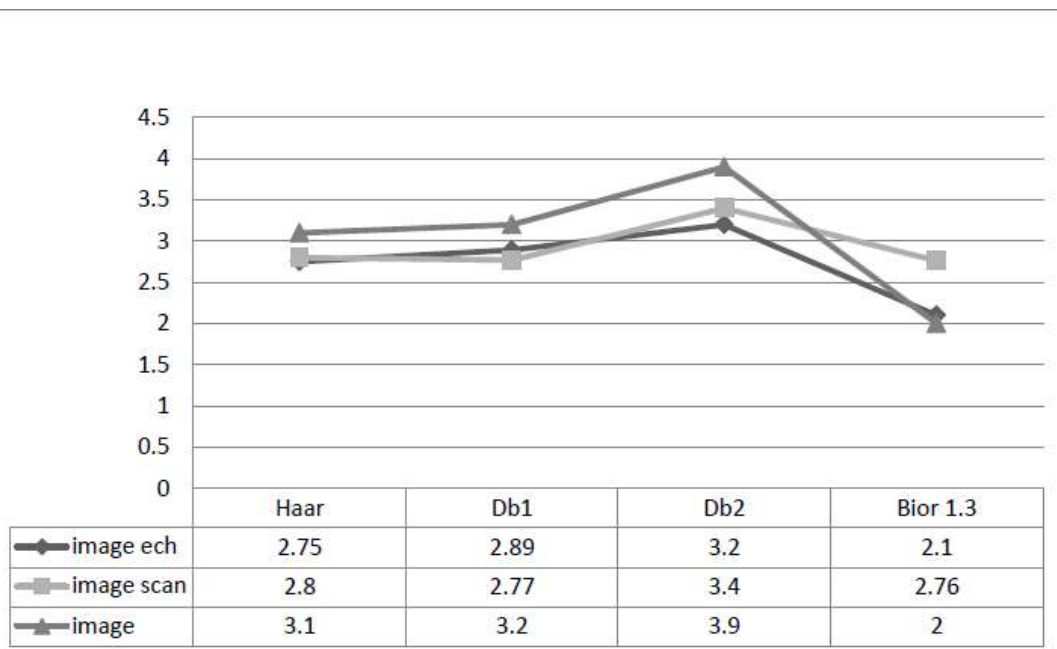


Figure 1 - Segmentation using different wavelets based on the Yasnoff measure

In our work, we use the Position of Missegmented Pixels Index: Yasnoff et al.'s measure. We conducted several experiments with different types of wavelets, and then applied the active contour segmentation (RSF). The Daubechies wavelets yielded better results, which supports the use of this wavelet family.

In terms of speed, we observed that the Db2 wavelet provides an optimal result.

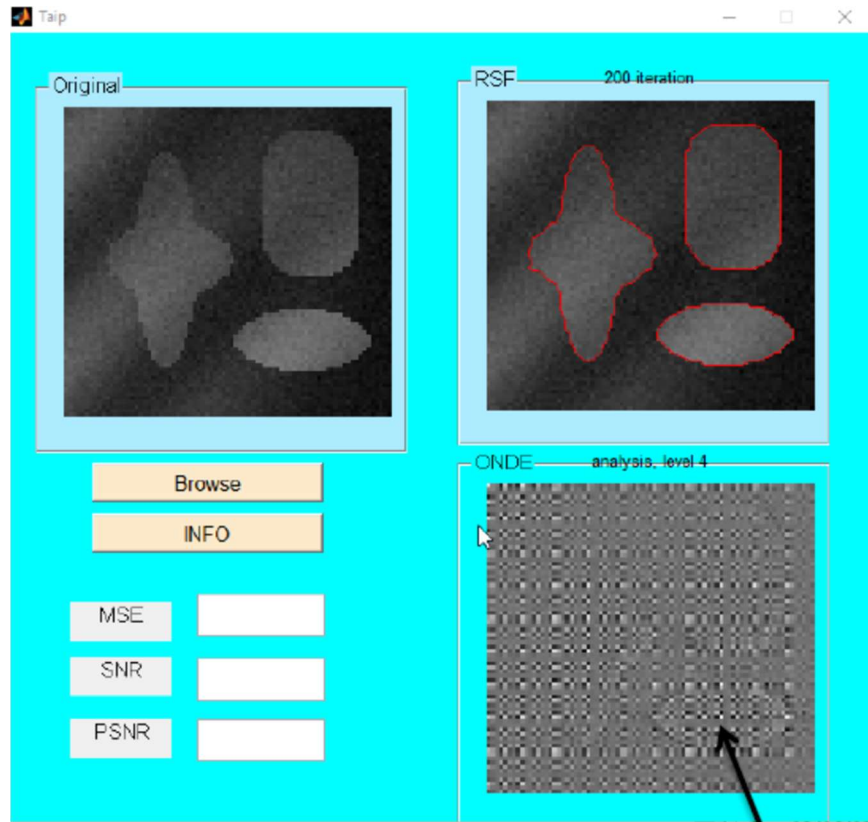
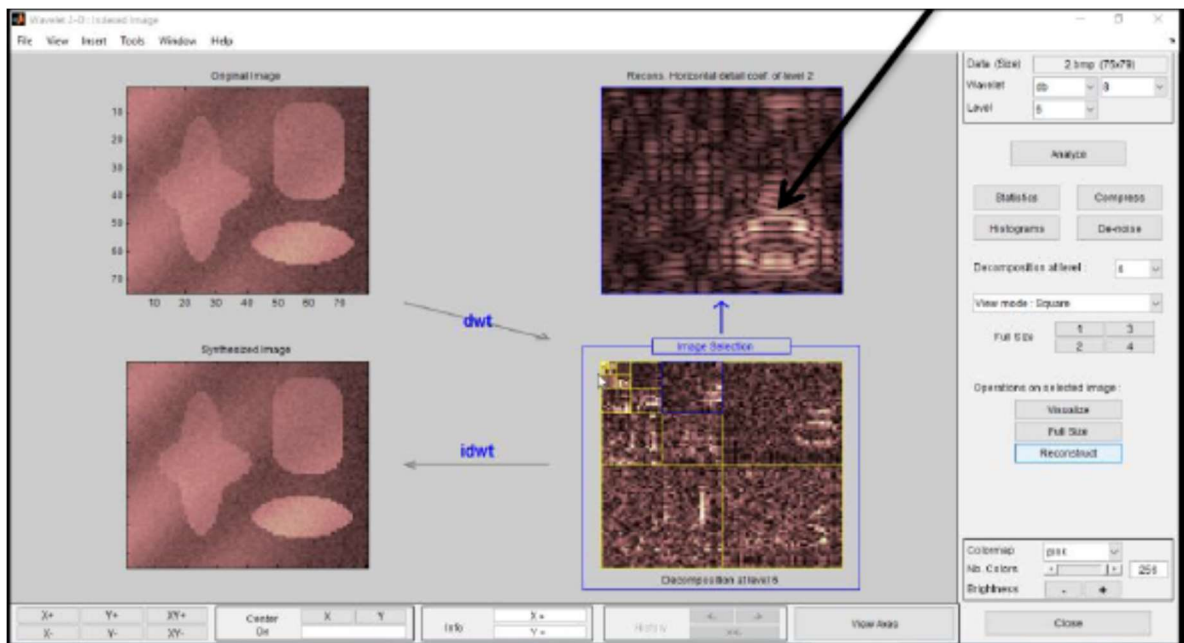


Figure 2 - Screenshot in phase 1



To assess the performance of the wavelet-based approach in terms of both speed and robustness, we compared it to a simple approach. It is important to note that the same contour technique is used in both approaches. The accuracy of the results is evaluated with respect to the exact contour of the shape to be segmented and estimated using the method described in [15].

b. Reconstruction:

Reconstruction of the deformed model at the higher resolution

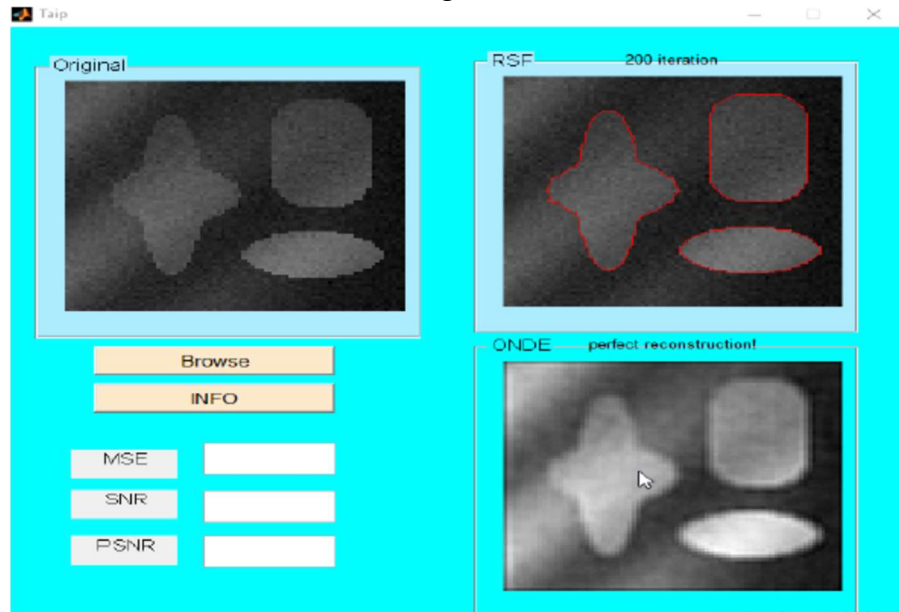


Figure 3 - Screenshot in phase 2

c. Adjustment of the model to the image by an active contour method

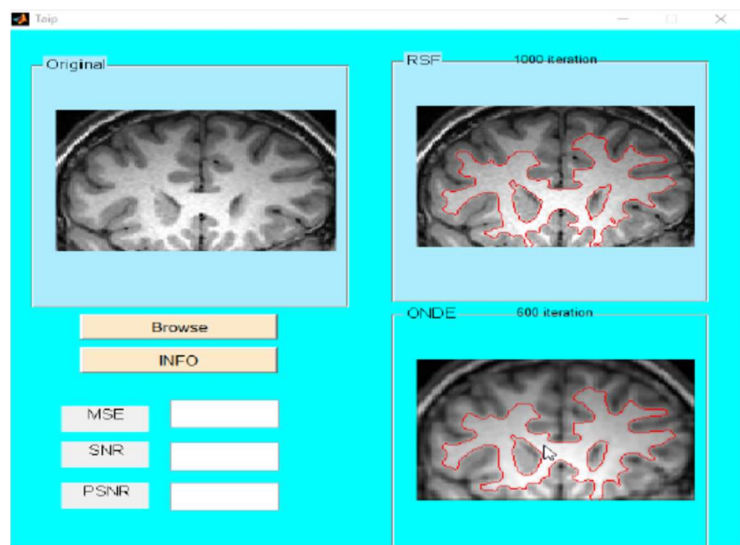


Figure 4 - Screenshot in phase 3

In some experiments, the segmentation result obtained by the simple approach is slightly more accurate than the one obtained by the wavelet-based approach. Considering the image details that we want to segment, the number of points in the initial contour is high. Additionally, the distance between two contour points is very small.

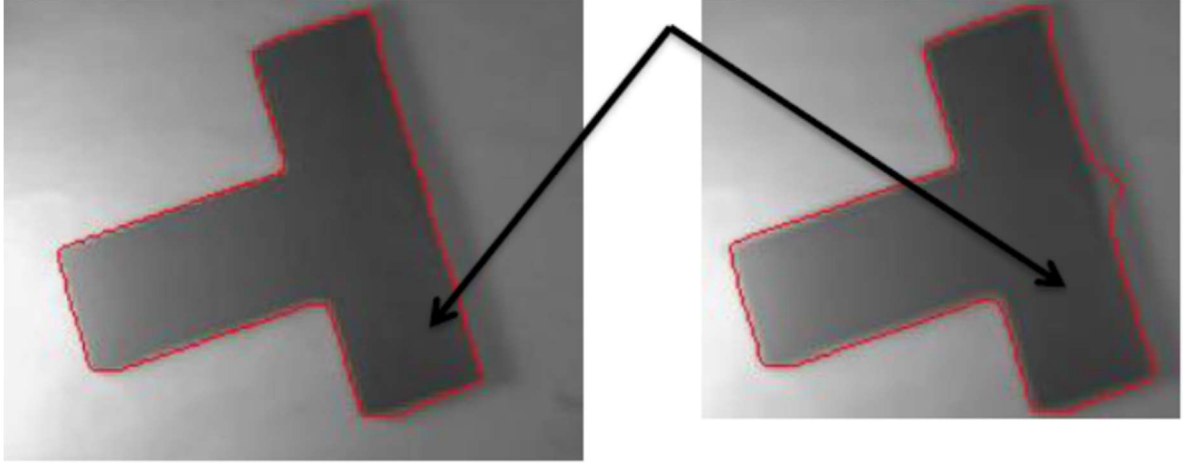


Figure 5 - Some segmentation errors

d. Tests in the presence of noise.

In the presence of Gaussian noise in the image ($\text{SNR} \sim 2$), the gradients that guide the contour evolution are disrupted. In the simple resolution approach, this leads to further slowing down of the contour evolution. The number of iterations required then increases significantly (Table 1). In the multiresolution case, the same evolution parameters as in the noise-free case are used. The result is obtained with a convergence time similar to the noise-free case, meaning it is 16 times faster than the simple resolution approach. The quality of the segmentation obtained with the wavelet approach is better than in the simple case. By increasing the level of noise in the image ($\text{SNR} \sim 5$), this effect is accentuated. With the same parameters in the simple resolution case, the result is quite disturbed and requires over 1000 iterations.

As can be shown, our hybrid technique constantly achieves the best results compared to all of the Classical techniques. The results of the experiments showed that the proposed technique was superior in terms of accurately obtaining segmentation from the original images.

Table.1 Performance of our approach compared to the classic approach.

	Classic approach						Our approach					
	iter	t	dice	jac	accurac	erreu	iter	t (s)	dic	ja	accuracy	erreu
		(s)			y	r			e	c		r
With	200	0.	0.65	0.14	0.6929	0.35	10	0.	0.9	0.781	0.95	0.
Noise		6	1	9			0	3			1	1

RSB~	400	4.	0.53	0.14	0.5428	0,98	90	1.	0.8	0.734	0.94	0.
2		3	2	9				1	3		1	2
RSB~	>100	/	0.32	0.14	0.3955	/	92	1.	0.8	0.625	0.92	0.
5	0		4	9				8	1		9	3

4. Conclusion

Segmentation of medical images remains an open area of research. It is said that the goal of image segmentation is to facilitate the extraction of its constituent elements. Therefore, subsequent tasks such as feature extraction, object position detection, or object recognition heavily depend on the quality of segmentation.

our study of segmentation enabled us to identify potential areas of further research:

- We can affirm that the use of wavelets enhances the performance of the active contour segmentation method with reasonable execution time.
- As a future perspective, we can suggest improving our results by integrating another method to delineate the processing area and eliminate noise or artifacts present in medical images.
- We also deduced that, based on the tested approach, cooperative segmentation is a method that achieves two fully compatible segmentations. It combines the advantages of each approach when used separately.

References

- [1]. Roobottom CA, Mitchell G, Morgan-Hughes G (November 2010). "Radiation-reduction strategies in cardiac computed tomographic angiography". *Clinical Radiology*. **65** (11): 859–67. doi:10.1016/j.crad.2010.04.021
- [2]. Dhouib, D.; Naït-Ali, A.; Olivier, C.; Naceur, M.S. (June 2021). "ROI-Based Compression Strategy of 3D MRI Brain Datasets for Wireless Communications". *IRBM*. **42** (3): 146–153. doi:10.1016/j.irbm.2020.05.001
- [3]. Perera Molligoda Arachchige, Arosh S.; Svet, Afanasy (2021-09-10). "Integrating artificial intelligence into radiology practice: undergraduate students' perspective". *European Journal of Nuclear Medicine and Molecular Imaging*. **48** (13): 4133–4135. doi:10.1007/s00259-021-05558-y
- [4]. Rishu. S; Ruarri J; Chaitanya. P (February 2023). " Multiphase segmentation of digital material images ". *Data-Centric Engineering* (2023), 4: e5 doi:10.1017/dce.2022.40. doi: 10.1017/dce.2022.40
- [5]. Kalaiselvi. T; Nagaraja. P (November 2016). " An Automatic Segmentation of Brain Tumor from MRI Scans through Wavelet Transformations". *International Journal of Image, Graphics and Signal Processing* **11**(11):59-65. doi: 10.5815/ijigsp.2016.11.08

- [6]. Verma. A. K., Patvardhan C., Vasantha Lakshmi. C.,(2015) “ Robust Adaptive Watermarking Based on Image Contents Using Wavelet Technique”, International Journal of Image, Graphics and Signal Processing, vol.2, pp. 48-55, 2015,
doi: [10.5815/ijigsp.2015.02.07](https://doi.org/10.5815/ijigsp.2015.02.07)
- [7]. Larbi, M.; Rouini, A.; Messali, Z.; Larbi, S. (September 2019). " Medical Image Segmentation Based on Wavelet Transformation and Level set method". Conference: 2019 International Conference on Applied Automation and Industrial Diagnostics (ICAAID)
doi: [10.1109/ICAAID.2019.8934970](https://doi.org/10.1109/ICAAID.2019.8934970)
- [8]. Larbi, M.; Messali, Z.; Rouini, A.; Larbi, S. (August 2019). " Image Segmentation Algorithm based on Level Set Method with Stochastic Constraint applied to Computed Tomography Images". *Electrotehnică, Electronică, Automatică* 67(2):52-61
- [9]. Larbi, M.; Messali, Z.; Rouini, A.; Larbi, S. (December 2020). " An Image Segmentation Model Using a Level Set Method Based on Improved Signed Pressure Force Function SPF". Proceedings of the 4th International Conference on Electrical Engineering and Control Applications, ICEECA 2019, 17–19 December 2019, Constantine, Algeria
doi: [10.1007/978-981-15-6403-1_87](https://doi.org/10.1007/978-981-15-6403-1_87)
- [10]. Xiao-Ping Zhang; M.D. Desai (August 2002). " Wavelet based automatic thresholding for image segmentation ". Proceedings of International Conference on Image Processing.
doi: [10.1109/ICIP.1997.647744](https://doi.org/10.1109/ICIP.1997.647744)
- [11]. Rinisha. B; Sulochana. W; Arun Kumar. W (July 2021). " A Wavelet-Based Segmentation Technique for Medical Images". Proceedings of International Conference on Image Processing. doi: [10.1007/978-981-16-1220-6_6](https://doi.org/10.1007/978-981-16-1220-6_6)
- [12]. Rinisha. B; Sulochana. W; Arun Kumar. W (February 2023). " An Image Segmentation for Different Medical Image Modalities using Wavelet Transform Technique". International Journal of Scientific Research in Science and Technology 10(1):292-307
doi: [10.32628/IJSRST2310134](https://doi.org/10.32628/IJSRST2310134)
- [13]. Larbi, M.; Rouini, A.; Larbi, S. (May 2022). " A Robust Stochastic Image Segmentation Model for Medical Images ". Conference: 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD). doi: [10.1109/SSD54932.2022.9955837](https://doi.org/10.1109/SSD54932.2022.9955837)
- [14]. Knoll, C, Alcaniz, M et Monserrat, C.(1999). "Outlining of the Prostate Using Snakes with Shape Restrictions Based on the Wavelet Transform. Pattern Recognition". 1999, 32, pp. 1767–1781. doi: [org/10.1016/S0031-3203\(98\)00177-0](https://doi.org/10.1016/S0031-3203(98)00177-0)
- [15]. Chen H.-L., Wang G., Ma C., Cai Z.-N., Liu W.-B., Wang S.-J. (2016). "An efficient hybrid kernel extreme learning machine approach for early diagnosis of Parkinson’s disease". *Neurocomputing* . 2016;184:131–144. doi: [10.1016/j.neucom.2015.07.138](https://doi.org/10.1016/j.neucom.2015.07.138)
- [16]. Zou KH, Warfield SK, Baharatha A, Tempany C, Kaus MR, Haker SJ, et al. (2004)."Statistical validation of image segmentation quality based on a spatial overlap index". *Academi Radiology*. 2004;11:178–89.
doi: [10.1016/S1076-6332\(03\)00671-8](https://doi.org/10.1016/S1076-6332(03)00671-8).

- [17]. Jaccard P. (June 2000). "The distribution of the flora in the alpine zone. New Phytologist". 2000;11(2):37–50.
doi: 10.1111/j.1469-8137.1912.tb05611.