

Statistical evaluation of application specific image segmentation algorithms

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Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: Image segmentation has been an area of interest for many researchers due to its ease of visual representation. Some segmentation algorithms work differently for different applications, which makes them widely applicable. For instance, the same kMeans algorithm produces unique and efficient results when applied to areas like plant disease segmentation, medical resonance imaging (MRI), breast cancer detection, etc. A segmentation algorithm is said to be effective if the extracted regions of interest (ROI) match the expected regions of interest. A difference between the expected and the extracted ROI images is termed as minimum mean squared error (MMSE). This MMSE must be minimized in order to improve efficiency of the segmentation algorithm. In order to reduce MMSE various algorithms have been proposed by researchers over the years, the performance of these algorithm is heavily dependent on the application context. Modern day imaging systems can work effectively only if a hybrid combination of these algorithms is used. Thus, it is becoming increasingly difficult for researchers and imaging system designers to select highly effective application specific segmentation algorithms for their deployments. In order to solve this issue, this text reviews various state-of-the-art image segmentation algorithms and compares them in terms of statistical parameters like MMSE, peak signal to noise ratio (PSNR), delay of segmentation, etc. This will assist researchers and imaging system designers to select best algorithms for their given applications, and thereby reduce the time needed to design these systems. This will also assist designers to further enhance the system performance by selecting application specific image segmentation algorithms.

Keywords: Image, segmentation, MMSE PSNR, delay, statistical

1. Introduction

Image segmentation is a very generic image processing problem that involves efficient conversion of image pixel data into regions of interest (ROI) as per the given application. An image segmentation algorithm can divide the image into one or more ROIs depending upon the thresholds set during the algorithm design. The general steps followed during design of any image segmentation algorithm can be observed from figure 1, wherein the flow of steps from image acquisition to final image segmentation are showcased. The image acquisition block is responsible for acquiring high quality images for segmentation. The sensor interface must be designed such that the captured images have minimum distortions in terms of camera noise, lens blur, etc. For majority of image segmentation applications, standard datasets are used in order to design the image acquisition block. The images from this block are given to a pre-processing unit, wherein algorithms like median filter, wiener filter, etc. are applied. These algorithms are responsible for noise removal from the images. Noise removal is a necessary step in any image segmentation application, because the noise in images disturbs the threshold and other parametric calculations for the next blocks.

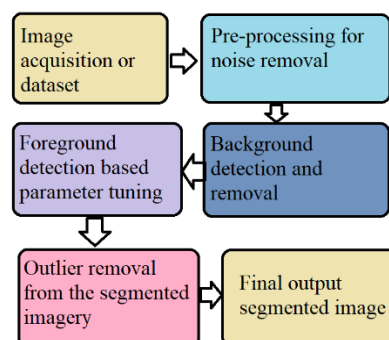


Figure 1. General steps in image segmentation

The pre-processed image is given to a background removal block. This block is responsible for evaluating pixels that have low variance w.r.t. other image pixels, and thus detecting the background map. This background map is subtracted from the image, and a coarse segmented image is formed. This coarse image is given to the foreground detection block, wherein application specific foreground detection algorithms are evaluated. These

algorithms vary in terms of colour, texture, shape or edge-based segmentation. The output of this step is a fine segmented image which is given to an outlier removal block where the final segmentation is done. The outlier removal block is optional for some applications where the image consists of only foreground and background parts. Finally, the obtained image is given to a MMSE evaluation block, where performance of the algorithm is evaluated and tuned if needed.

The next section studies some of the recently proposed segmentation techniques and evaluates their performance in terms of common parameters like MMSE, PSNR, delay of segmentation, etc. This is followed by the application based statistical comparison of these techniques and recommendations to further improve the efficiency of these algorithms. Finally, this text concludes with some interesting observations about these algorithms, and suggests further research in the given area of application.

2. Literature Review

A large amount of research has gone into effective segmentation of remote sensing images. These images are usually taken from satellites and other high altitude imaging devices. Segmentation of these images requires an additional fusion step, that combines image data from different spectral bands into a single image. This combined image is also called as fused image and is given as input to the blocks mentioned in figure 1. A combination of clustering, graph segmentation and Bayesian approaches for satellite image segmentation is mentioned in [1], wherein feature vectors are evaluated using spectral block averages from the image. The algorithm performs segmentation using the following 4 steps,

- Initially all the image spectral components (R, G and B) are divided into blocks of equal size. The average of each of these blocks are taken in order to generate an image level feature vector.
- This feature vector is given to a simple k-means based clustering algorithm, which finds out different clusters for the feature vector for rough image segmentation.
- The clustered image is given to a Bayesian model in order to evaluate a preliminary segmented image.
- Finally, a graph-based fine segmentation method is deployed for producing the output segmentation image

The block diagram for this system can be observed from figure 2, wherein a detailed description of these techniques is mentioned.

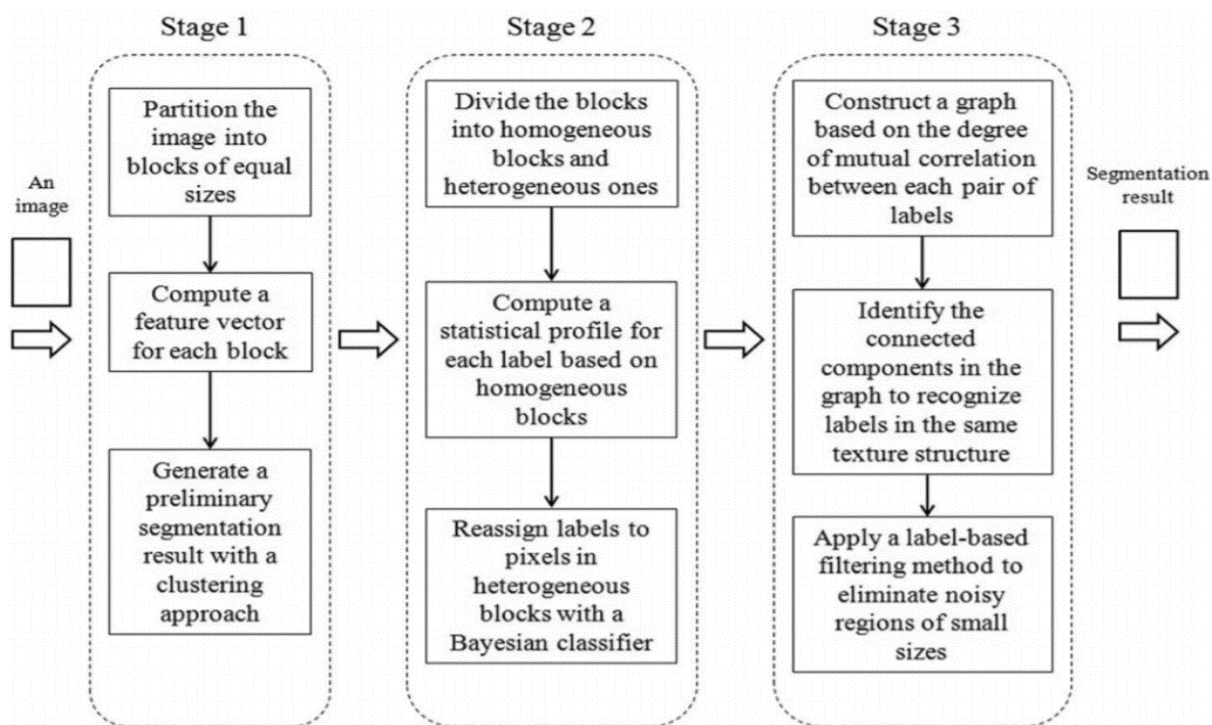


Figure 2. Process flow for segmenting satellite images [1]

This algorithm has good segmentation performance, but requires high delay due to the involvement of multiple processing layers. This delay can be reduced using pre-trained neural network models, which require one-time training and can be used for multiple evaluations. Such a neural network model based on semantic segmentation

can be observed in [2], wherein a series of feed-forward, back propagation and convolutional layers are used in order to obtain the final segmented image. Due to the use of such a complex network structure a high peak signal to noise ratio along with a low delay is observed. The evaluation of this model is done on limited datasets, and thus elaborate evaluation is needed for real-time testing. Moreover, due to the one-time training complexity of this algorithm, it is necessary to re-train the algorithm in case of decreasing performance or whenever a new dataset is used. Thus, in order to remove the dependency of the system on re-training a universal algorithm for segmentation must be evaluated. Such an algorithm that uses Intuitionistic Fuzzy C-means approach is proposed in [3]. In this approach, a non-parametric Lorentzian Redescending M-estimator is used along with basic colour feature sets. A differentiation between the obtained image and the expected segmentation image is made in order to train the feature sets. This training allows the system to have better peak signal to noise ratio (PSNR) and reduced segmentation error. A combination of [1] and [2] is done for developing a robust neural network-based algorithm to segment satellite imagery. It uses a combination of complex valued neural networks (CVNN) along with complex valued auto encoder (CVAE) in order to reduce the training loss for the input image dataset. The flow diagram for this system can be observed from figure 3, wherein a combination of multiple CVAE's is done in order to produce the final segmentation image evaluation model. The process guarantees 85% segmentation accuracy along with reduced processing delay for segmentation.

A combination of different meta-heuristic algorithms for better image segmentation can be observed from the study in [5]. In this study a series of image segmentation algorithms that use meta-heuristic approaches like cuckoo search (CS), bat algorithm (BA), artificial bee colony optimization (BCO), firefly algorithm (FA), social spider algorithm (SSA), whale optimization (WO), moth-flame optimization (MFO), grey wolf optimization (GWO) and particle swarm optimization (PSO) are applied to existing non-meta-heuristic algorithms like edge-based segmentation, region-based segmentation, data-clustering-based segmentation to improve their accuracy. Out of these techniques the PSO and BCO approaches are found to be the most optimum across a set of different image datasets. Moreover, a multi-objective optimization version of these algorithms is also suggested for quality improvement and colour image segmentation. It is observed that the PSNR for multi-objective algorithms is lower than the single-objective algorithms because multi-objective algorithms also optimize the delay and rank needed for the entire segmentation process.

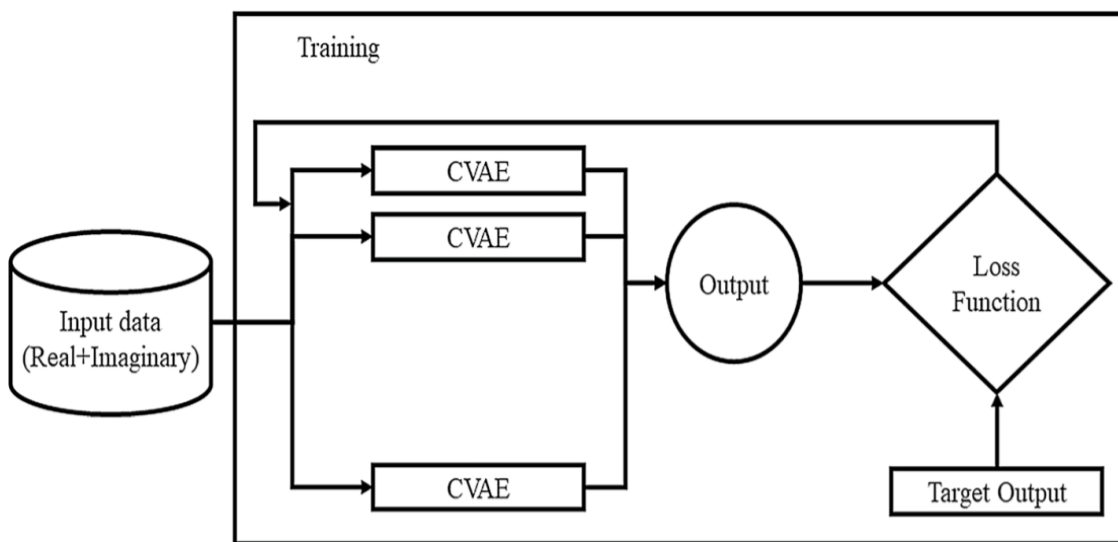


Figure 3. CVAE based model for reduced error during segmentation [4]

The performance of these meta-heuristic approaches can be further improved with the help of convolutional neural network (CNN) based approaches. Such an approach is mentioned in [6], wherein Adaptive Dropout Depth Calculations are done on medical images for improved performance. The system uses the following flow in order to evaluate segmented image data,

- Input images are given to the system and are pre-processed for noise removal
- Optimized CNN models are applied in order to obtain the initial coarse segmented image
- Depth calculations are done based on adaptive dropout model, which differentiates foreground and background parts of the images with quantification
- Based on regions with minimum depths the final segmented image is produced at the output

Due to this process, the system produces high PSNR, but has large delay requirements because of depth evaluation. In order to reduce this delay, a wavelet-based algorithm that uses simplistic calculations for image segmentation as mentioned in [7] can be used. Based on this algorithm, different wavelet features like Haar, Edge Orientation Histograms (EOH), and their combination is used. It is observed that a combination of these features produces high quality segmentations for general purpose image datasets.

In order to optimize different segmentation parameters, the work in [8] can be considered. It uses a combination of Genetic Algorithm and Otsu method for effective segmentation of general-purpose images. The system is tested on a limited set of images, and thus is not applicable for real-time use cases. But the idea of using Genetic Algorithm for image segmentation is solid, and must be considered while optimization of segmentation algorithms. Another simplistic method that uses non-parametric clustering for segmentation is proposed in [9]. This method uses direct image pixels in order to evaluate different cluster sets based on hierarchical connected components technique. Due to the usage of hierarchical connected components, the image segmentation accuracy of the system improves for certain set of images. This set consists of images that has visible connected components, but is not applicable for images where these components are hidden or not present.

From the researches reviewed up to this point, it can be observed that machine learning models are one of the most optimum techniques when it comes to image segmentation. A survey of such techniques along with their comparative performance evaluation can be observed from [10], wherein methods like support vector machine, artificial neural networks (ANN), CNN and recurrent neural networks (RNN) can be observed. An example of a complex RNN that uses a combination of multiple CNNs can be observed from figure 4, wherein layers like input, activation, convolution, pooling, fully connected, up-sampling and output are shown. The RNN model is the best suited model for image segmentation, due to the fact that it utilizes the best results from each CNN in order to produce the final segmentation output. A study on medical datasets like lung image database consortium image collection, liver tumour segmentation, 3D image reconstruction for comparison of algorithm database, etc. is used for performance evaluation. It is observed that RNN and CNN outperform any other methods when it comes to PSNR, rank and delay performance. An application of these methods to plant segmentation can be observed from [11], wherein a neural network is used on different plant datasets for segmentation. The performance of NN is found to be better than methods like discrete cosine transform (DCT), latent discriminant analysis (LDA), Random Forest RF) and Support Vector Machines (SVM).

Even though the performance of neural networks is high for most applications, but this performance can be further improved with the help of fuzzy clustering-based methods like the one mentioned in [12]. Here, a combination of fuzzy logic with C-means algorithm is done along with certain advanced pre-processing steps in order to obtain the final segmented image.

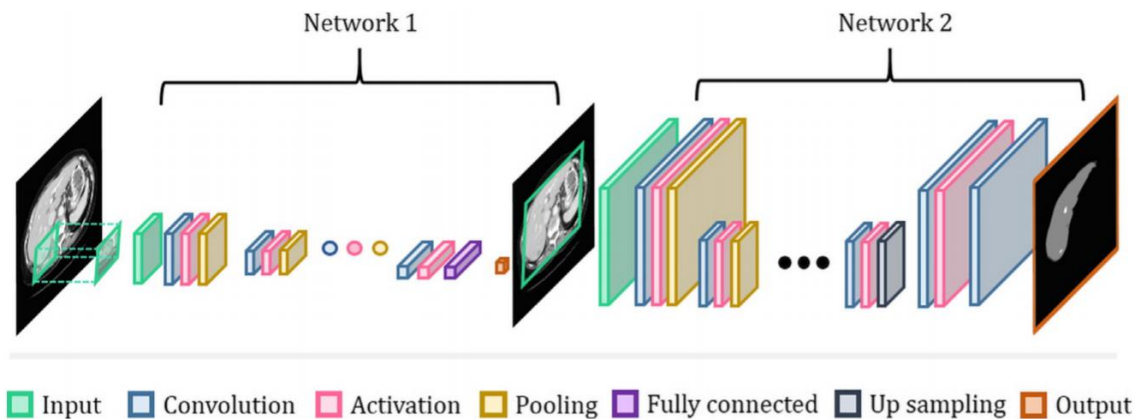


Figure 4. Architecture of RNN for segmentation [10]

A good level of performance is obtained with the help of extended FCM (eFCM) when evaluated on medical resonance imaging (MRIs). This performance can be further extended using a Pythagorean FCM method mentioned in [13], wherein Pythagorean fuzzy sets are used for image representation, and the results from these sets are given to c-Means for final segmentation. As a result of the usage of Pythagorean fuzzy sets, the delay increases but there is an improvement in the PSNR and rank performance of the system. Further extension of this method to specific MRI images using Quantum-Inspired Modified Genetic Algorithm can be observed in [14]. Here, every pixel is converted into quantum data, and this data is given to the Modified Genetic Algorithm (MGA) for better performance. The MGA method improves the performance of a FCM algorithm by taking delay and PSNR as a part of fitness calculations. As a result of this, the final PSNR improves along with moderate delay performance. This method is applicable for grey scale images, which has a limited area of application. In order to

extend the method to colour images, a novel Student's t-based method based on density peaks clustering and super pixel segmentation is proposed in [15]. This method works using the following steps,

- Perform automatic and constrained simple non-iterative clustering to obtain super pixels
- Evaluate central colour values of super pixel
- Evaluate the value of closeness using student's t-kernel method
- Re-formulate the super pixel with this closeness value
- Obtain a label vector and perform label matching to finally output the cluster map

This cluster map is super imposed with the original image to get the final segmented image. The method provides superior PSNR performance, but has high delay requirement due to evaluation of super pixels. While super pixels are very effective for providing high quality image segmentation, but their efficiency can be improved by using them with deep learning methods. The work in [16] and [17] proposes the application of such deep learning methods to medical imaging and compares the effects of application of super-pixels and non-super-pixels. They have compared the performance of 2D CNNs, 2.5D CNNs, 3D CNNs, RNNs and V-Nets in order to find out the best deep learning method for image segmentation. From their research it is evident that CNN based models are most effective for medical image segmentation. The architecture of a high accuracy CNN used in medical imaging can be observed from figure 5, wherein layers like activation, feature maps, activation maps, etc. are connected in tandem to get the final segmented image. The application of deep learning models is further extended to optical microscopy in [18] for searching 2D textures in images. The algorithm is used for 1024px X 1024 px micro-scope images, and different texture-based materials are segmented from the image.

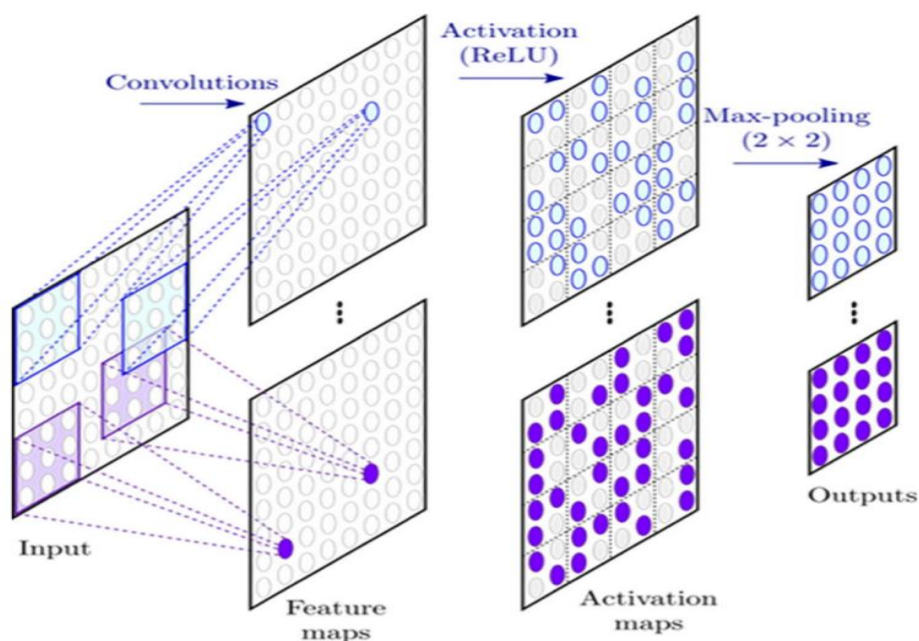


Figure 5. A highly accurate CNN for segmentation [16]

The application of this technique can be at airports for checking of security baggage, or for scanning of objects present with a person during International travel. An instance of such this algorithm based on ResNet architecture can be observed from figure 6, wherein the ResNet101 architecture is used along with region proposal network (RPN) for segmented mask generation. The obtained classes and bounding box values are stored inside a database for final segmentation.

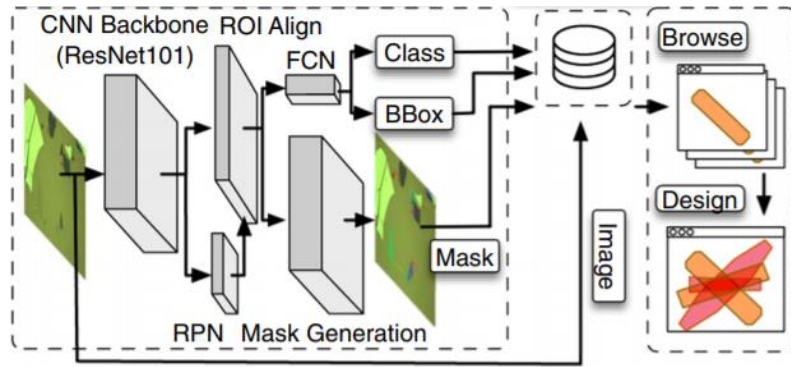


Figure 6. RPN and CNN for image segmentation [18]

Due to the combination of RPN with CNN the final PSNR values are very high, and due to the use of ResNet101 architecture, the delay of segmentation is low. But, the application area of this algorithm is limited to optical microscopic images, therefore the algorithm must be tested on other applications before using it for real-time applications. The concept of convolution can be applied to simple algorithms like k-Means in order to improve its efficiency. The work in [19] extends the concept of convolution to adaptive k-Means algorithm in order to develop the convolutional modified adaptive k-Means (CMAk-means). The flow of this entire process can be observed from figure 7, wherein images from different domains are taken and their histogram is evaluated. The output of this histogram is given for calculation of amplitude threshold, which is used for initial background detection. This image is given to a 2D convolutional block to generate initial seed for the k-Means algorithm. Finally, a post processing unit is activated in order to get the final segmented image. This approach is tested on a multitude of image datasets, and high PSNR and moderate delay values are obtained. Some of the other methods where convolution can be applied for better performance can be reviewed from [20], wherein methods like Random-walk, Region Growing, super-pixel, seed methods, etc. are compared. All of these algorithms can be improved using convolution operations similar to [19], or they can also be improved using the nature inspired optimization approaches as mentioned in [21]. They suggest that the Cultural Algorithm (CA) along with Cuckoo Search Algorithm (CSA) are the best optimization methods to improve the segmentation performance.

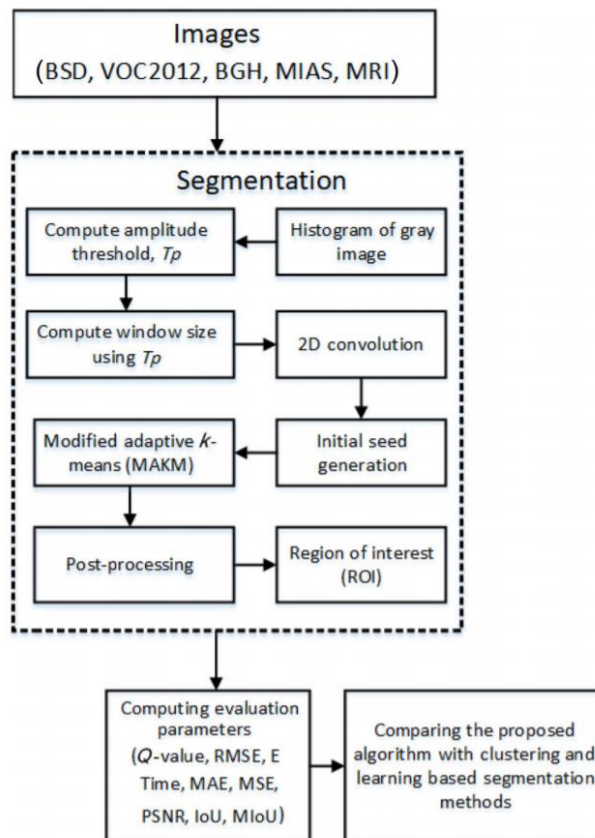


Figure 7. Convolutional Modified Adaptive k-Means Approach (CMAk-Means) [19]

Another literature that showcases the superiority of meta-heuristic algorithms like Flower Pollination (FP), Differential Evolution (DE), etc. can be observed from [22], wherein it is observed that a modified version of DE algorithm named as Improved DE or IDE is one of the best algorithms for performing image segmentation. While these algorithms give good performance, the work in [23] suggests that usage of PSO, BCO and Ant Colony Optimization (ACO) in tandem can further improve segmentation performance for general purpose imagery. The overall system flow can be observed from figure 8, where combination of these algorithms along with their application at each stage is mentioned in details. The system initializes different parameters for ACO, PSO and BCO algorithms, then uses a stochastic process for threshold evaluation. After this, three different threshold evaluation stages are applied in order to optimize the segmentation performance at each stage.

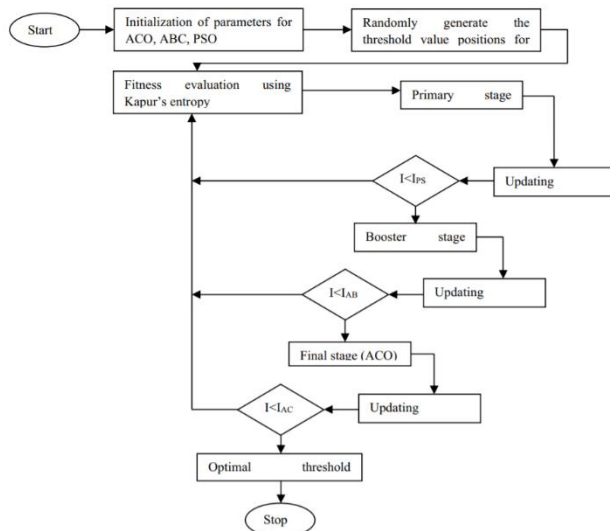


Figure 8. Hybrid combination of meta-heuristic algorithms for better system performance [23]

Finally, the results from all these stages are combined in order to get the final segmented image. While the performance of this algorithm is good, it can always be improved using CNNs and RNNs. For instance, the work proposed in [24] uses a fully connected CNN model with conditional random fields in order to segment MR images. To segment brain tissues the architecture described in figure 9 is used, wherein CNN forward layers and reverse layers are showcased.

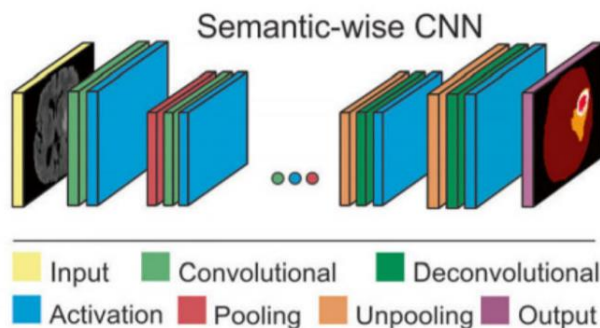


Figure 9. Forward and inverse CNN for segmentation of MRI [24]

Using this dual architecture, the final image segmentation task is performed. It uses a pixel-to-pixel mapping for CNN training in order to produce the output segmented image. The proposed approach has high PSNR and high delay requirement due to this dual level architecture.

A low complexity and moderate PSNR approach for segmentation of general-purpose imagery is defined in [25]. Here, adaptive morphological reconstruction (AMR) is combined with seeded image segmentation in order to improve the segmentation performance. Here a triple AMR operation is performed followed by gradient magnitudes, region minima evaluation and local seed evaluation to get the final segmented image. This AMR technique can be further improved using automatic fuzzy clustering approach like the one mentioned in [26].

Using this approach, the image pixels are converted into super-pixels. The super-pixels are given to the density peak algorithm for effective clustering. This initial clustering data is given to fuzzy C-means (FCM) for improved segmentation efficiency. Due to the combination of density peak, super-pixels and FCM the final PSNR is improved, but the delay of processing increases due to these different mutually dependent algorithms.

The work on seeded region growing (SRG) in [25] is extended by the work in [27] and is used for smoke detection application. It uses a combination of colour space conversion along with thresholding to improve the efficiency of SRG. The algorithm uses automated seed point detection with the help of background subtraction and motion detection for smoke videos. A high efficiency with low delay is obtained for this particular application, thus the algorithm needs to be extended for different applications in order to test its efficiency for real-time segmentation scenarios. In order to expand the SRG algorithm to other domains, the research in [28, 29] must be referred. Authors have suggested different areas in which any given algorithm must be modified in order to improve the overall applicability of the algorithm to the given application. The use-case of this study can be observed in [30], wherein a brightness preservation algorithm is applied for MRI segmentation. The algorithm uses optimized weighted bi-histogram equalization in order to initially pre-process the image. This pre-processed image is given to a fuzzy level set algorithm for final segmentation. Overall flow for this process can be observed from figure 10, wherein output imagery is obtained from the fuzzy level set block.

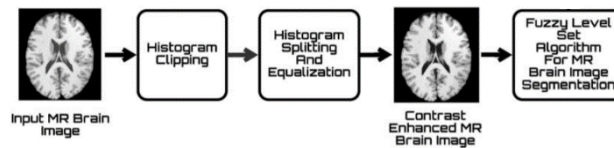


Figure 10. Bi-histogram equalization with fuzzy sets for improved segmentation performance [30]

The algorithm produces high PSNR with low delay and improved rank performance for MR imaging, and must be expanded to other applications with modifications in threshold calculations. In order to do this, the existing algorithm can use concepts from deep learning strategies like the one mentioned in [31], wherein a CNN is used for segmentation of nuclei regions from microscopic images. Another deep learning mechanism is suggested in [32], wherein self-organizing maps (SOM) are used in tandem with node-growing algorithm in order to segment multi-colour imagery. This algorithm takes growing data from first best matching unit and second-best matching unit in order to produce minimally trained SOM network. This SOM network is trained with other best matching data matches in order to produce the final resulting image. This improves the overall segmentation performance in terms of PSNR, but requires larger delay due to continuous training. The performance evaluation of these algorithms in terms of PSNR, delay and ranking parameters is given in the next section.

3. Statistical Analysis

In order to perform the statistical analysis of the reviewed systems, the following parameters were evaluated,

- Peak signal to noise ratio (PSNR)

The PSNR value is evaluated using a metric termed as minimum mean squared error (MMSE). This MMSE value is calculated using the following formula,

$$MMSE = \frac{\sum \sum I_1 - I_2}{M * N} \dots (1)$$

Where, I_1 is the extracted segmented image, and I_2 is the expected segmented image, while ‘M’ and ‘N’ are number of rows and columns in the image. Using this value, the PSNR is evaluated as follows,

$$PSNR = 20 * \log_{10} \left(\frac{255}{MMSE} \right) \dots (2)$$

A high value of PSNR indicates that the error between expected and extracted images is low. Therefore, it is expected that an algorithm should have a high level of PSNR.

- Delay

Delay indicates the time needed by the algorithm between taking an input image and producing the output image. It is evaluated using the following formula,

$$Delay = T_{processed} - T_{unprocessed} \dots (3)$$

Where, $T_{processed}$ is the time when the image is just processed, and $T_{unprocessed}$ is the time just before the image is given for processing. A low value of delay is expected for any real-time algorithm

- Rank

Rank is a measure of closeness between the expected image and the extracted image. A low value of rank is expected from a segmentation algorithm.

The referred texts do not have a similar comparison base which is needed for performing statistical evaluation. Thus, this evaluation is done by taking an average of all the readings observed in the reviewed texts. Average readings give an approximate estimate about the performance of reviewed algorithms when applied to different kinds of datasets, and thus it is used for evaluation. The following table 1 indicates the performance evaluation of the reviewed algorithms.

Method	Appli-cation	PSNR (dB)	Delay (s)	Rank
Clustering with Bayesian processing [1]	Satellite	28.5	15.4	1.67
Cascaded neural networks [2]	General images	29.2	1.3	1.65
Intuitionistic Fuzzy C-means [3]	General images	29.1	0.76	1.66
CVAE [4]	Satellite images	28.5	3.67	1.54
PSO Single Objective [5]	General images	32.6	9.25	1.96
PSO Multi Objective [5]	General images	30.5	2.69	1.59
BCO Single Objective [5]	General images	31.4	10.9	2.1
BCO Multi Objective [5]	General images	29.8	2.94	1.68
CNN with Depth Maps [6]	Medical images	33.5	13.2	1.47
Wavelet with Haar and EOH [7]	General images	28.4	0.65	1.97
Clustering with connected component [9]	Application Specific images with visible connected comp-onents	24.6	0.91	2.55
SVM [10]	Medical imaging	28.9	2.45	1.94
ANN [10]	Medical imaging	29.1	6.19	1.68
CNN [10]	Medical imaging	33.6	3.71	1.59
RNN [10]	Medical imaging	34.9	4.59	1.43
NN [11]	Plant datasets	31.4	2.26	1.61
EFCM [12]	MRI imaging	26.1	1.04	1.98
PyFCM [13]	General images	27.3	2.64	2.01
Quantum MGA based FCM [14]	MRI imaging	28.7	2.18	1.85
Super pixel with Student's t-based density peaks clustering [15]	General colour imaging	29.5	15.6	1.94
2D CNN [16]	Medical imaging	32.5	3.84	1.57
2.5D CNN [16]	Medical imaging	33.1	4.68	1.56
3D CNN [16]	Medical Imaging	33.7	5.23	1.54
RNN [16]	Medical Imaging	34.2	5.16	1.49
CNN with RPN [18]	Optical micro-scopic images	34.5	2.91	1.48
MAC-kMeans [19]	General purpose imagery	31.5	4.3	1.71
Artificial tree [21]	General purpose imagery	22.5	15	1.9
Genetic Algorithm [21]	General purpose imagery	24.3	70	1.95
PSO [21]	General purpose imagery	27.5	109	2.26
CA [21]	General purpose imagery	28.5	55	1.93
CSA [21]	General purpose imagery	26.3	172	1.97
DE with FCM [22]	General purpose imagery	25.2	15.7	1.91
IDE with FCM [22]	General purpose imagery	27.9	9.4	1.74
ACO, PSO and BCO [23]	General purpose imagery	29.1	30.4	1.67
Dual CNN [24]	MRI	32.5	25.1	1.59
AMR with Seeded region growing [25]	General purpose imagery	27.6	5.9	1.85
FCM with DP [26]	General purpose imagery	28.2	13.5	1.91
Intelligent SRG [27]	Smoke detection	31.4	1.2	1.56
Weighted Histogram with Fuzzy Set Theory [30]	MRI	30.5	0.94	1.71

Table 1. Comparative statistical analysis for the reviewed algorithms

From this comparison it is evident that CNN and RNN based approaches outperform other approaches in terms of PSNR and Rank performance. But there is need to work on their delay performance for real-time application. The PSNR performance can be visualized using figure 11, wherein neural network-based approaches produce best possible segmentation.

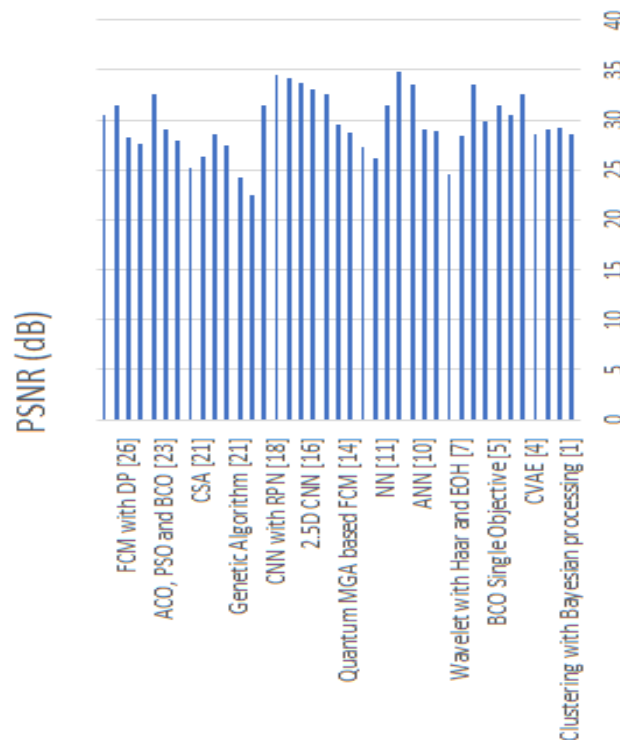


Figure 11. PSNR performance of reviewed algorithms

Thus, for effective segmentation NN based approaches are best suited, but delay performance can be improved.

4. Conclusion and future scope

From the statistical performance evaluation, it can be visualized that neural network-based systems have better PSNR performance than other methods. A performance jump of more than 20% is observed in terms of PSNR and rank values when CNNs and RNNs are compared with methods like kMeans and SRG. The performance of CNNs and RNNs can be further improved with the help of meta-heuristic methods like GA, CA, CSA and PSO. Moreover, it is also recommended that other variants of CNNs be used in conjunction with the given meta-heuristic approaches in order to further enhance the PSNR performance. Delay performance of these networks can be improved, thus it is recommended that researchers should search for effective ways in which delay can be reduced to improve the real-time applicability of these systems.

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