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*Original Article*

# An Effective Segmentation of MRI Images Combining Threshold and Hybrid Particle Swarm Optimization (HPSO-T) for Lung, Bone and Brain (LBB)

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***Abstract*** *- Segmentation in medical imaging is one of the fundamental problems in image processing. Perceptual completion and recognition during picture segmentation are the issues with image segmentation. Machine vision-based image threshold segmentation is an essential detecting tool. The issue of time consumption arises with the traditional threshold picture segmentation method. However, optimization techniques can help to resolve these problems. An effective optimization technique is needed to determine the ideal threshold. The thresholding will become more computationally intensive with increasing thresholds. This research proposed Hybrid Particle Swarm Optimization with Thresholding (HPSO-T) technique used for image segmentation to assess the MRI medical Image for detecting and managing various tumors in Lung, Brain and Bone-(LBB). This work extracts the MRI scan pictures using the LBB data acquired from the Kaggle website. The suggested segmentation methodology outperforms the other two segmentation approaches in the market with a Dice Index of 0.93.*

***Keywords*** *- Segmentation, MRI images, LBB, HPSO-T, Optimization.*

## 1. Introduction

Segmentation is recognized as one of the most critical processes in interpreting images. It divides a digital picture into several distinct uniform sections (pixel sets, sometimes referred to as "super pixels"). Partitioning a picture into a more manageable format for subsequent processing is the aim of segmentation. Locating boundaries (lines, curves, etc.) and objects is its use. The segmentation technique is significant in image processing and has been effectively employed in several fields, such as industrial production, medical image processing, and pattern recognition. In the last ten years, improving picture thresholding has received greater emphasis than ever. Thresholding is a segmentation technique that divides pixels into sections according to their luminance level while considering threshold values. Bi-level and multi-level thresholding are two levels of thresholding, which is a complicated process that depends on the segmentation requirements. High intensity pixel values in bi-level thresholding are regarded as objects, while the other pixels are regarded as backgrounds.

The threshold value determines which pixels are selected; if a pixel is below the threshold, it is assigned to a particular group; if the threshold is inadequate, it gets a different category. There will only be two colours in the bi-level threshold's final output. In contrast, several region pixels are divided using various levels of threshold in multilayer thresholding to depict the item in a picture. Thus, the finished picture has the same attributes as the original but with better ones.

The method of selecting the best threshold value for an image is typically used to summarize an image thresholding problem. Each image has a unique threshold value defined by the image spectrum. Otsu and Kapur's approaches are among the best at choosing the ideal threshold [1]. Researchers have focused much on PSO since it is an efficient swarm intelligence technique for picture segmentation problems. Compared to other ECs, the population's collective experience is referred to as the instructional element and denoted by pbest and gbest in PSO, drives the particle search direction, then has a rapidly increasing convergence rate, indicating that it can approach optima more quickly than ECs. Early convergence, a drawback of PSO, causes iterations to become stuck in optima, particularly when dealing with multimodal and multi-dimension issues.

The prior investigation indicates that two primary aspects influence PSO's search capability. The initial one is the particle's leading point that determines the direction of the population's evolution. Another factor is that throughout iterations, each member of the population's search capacity is limited by the particles' ability to leap. Certain works aim to keep the convergence rate constant while improving the PSO's capacity for worldwide exploration. Using these approaches, particles can conduct fine-grained and precise searches on a desirable area by defining it and then implementing a suitable jump technique. In actuality, the jumping technique is mostly responsible for PSO's worldwide searching capacity, and other tactics yield radically varied outcomes when applied to an optimization issue. Moreover, a particle's learning element chooses the object it should learn from. Following this, it also affects the particle's step size. Finally, as per the definition of PSO, elements are recognized as a separate or collective encounter after all their parameters are enhanced. This should lead certain aspects to fall behind the overall component's progress.

### *1.1. Research Gap and Problem Statement*

Traditional threshold segmentation mainly includes manual selection threshold method and automatic selection threshold method. The manual selection threshold method has a certain subjective blindness in solving the optimal segmentation threshold. The automatic selection threshold method generally includes an iterative method, maximum between-class variance method and maximum average information entropy method. The three methods objectively solve the optimal segmentation threshold through the adaptation function, and they cannot effectively deal with the uncertainties in image segmentation.

Zhu Liangkuan et al. [1] proposed forest canopy image segmentation based on an improved 3-D Otsu method. The algorithm's core is to use the knowledge of posterior probability to process the uncertainty in the image. Lei Xiangxiao et al. [2] proposed image segmentation based on equivalent 3-D entropy and whale optimization algorithms.

The entropy theory is used to measure the uncertain factors in the image. Finally, the whale optimization algorithm is used to improve the algorithm's efficiency. Nabanita Mahata et al. [3] segmented 3-D brain magnetic resonance images by minimizing global and local entropy space constraints and also used entropy to process image uncertainty. Xiaofeng Yue et al. [4] used the hybrid bat algorithm to segment the image.

The algorithm combines genetic crossover operations and smart inertia weight and uses the between-class variance and Kapur entropy as the objective function to solve the optimal segmentation threshold. The common point of the segmentation algorithms proposed by the above scholars is to use posterior probability to solve the uncertainties in image segmentation. But in practice, the posterior probability cannot effectively deal with the uncertainty in image segmentation

This paper describes the proposed HPSO-T technique for image segmentation to assess the MRI medical Image for detecting and managing various tumors in LBB.

## 2. Literature Review

This section's brief literature study overviews current developments in multifaceted picture thresholding techniques. In the last section, the approaches are reviewed, the performances are examined in light of the findings, and the conclusions are distilled into the study results. The gravitational search strategy was introduced in a unique two-dimensional histogram-based thresholding technique [6]. The Levy Flight Firefly technique was integrated into an enhanced fuzzy entropy based multilayer thresholding strategy [7] for image colour segmentation [of]. Better thresholding values are produced, and the suggested method minimises the fitness function, which considers similar entropy values for the entire region.

In [8], a multilayer thresholding method that utilizes variational model decomposition was introduced to delineate colored images efficiently. The described threshold selection method breaks down the visualization into several smaller models and presents the optimized Otsu's function as an objective. In this study effort, a hybrid algorithm for optimization combining the ant colony and swarm optimization algorithms is proposed to reduce error, increase optimum threshold detecting efficiency, and shorten search times. The ant colony optimization approach is outlined in [9]. It is used to improve the discovery of salp swarm optimization and the utilization of features to determine the ideal threshold for the image provided. With an emphasis on databases of lung CT scans and chest X-rays, this paper offers a thorough analysis of the effectiveness of PSO in conjunction with the preprocessing of HE for the segmentation of medical pictures. The efficiency of the PSO process is shown by its cost values; for complicated lung CT scan pictures, in particular, HE preprocessing significantly stabilizes and improves convergence [10].

Medical image analysis has traditionally been based on conventional segmentation techniques [11]. These techniques include detecting edges, region development, and thresholding methods [12, 13, 14]. A comparative evaluation of thresholding methods for medical imaging segmentation was carried out [15], and the results emphasized the methods' ease of use and limits when dealing with intricate intensity changes [16]. A subset of researchers has studied the potential and difficulties of region-growing-based segmentation [17], especially when dealing with complicated structures like brain tumor images [18, 19]. Due to this investigation, more reliable methods are now needed to handle the nuances and complexity of these images [20]. Our research extends PSO's application to the particular field of medical picture segmentation, a groundbreaking move in the field of medical image analysis [21]. Considering PSO's natural ability to explore complex search areas, this strategic expansion fits perfectly with the intricacies frequently present in healthcare pictures characterized by sound, uneven lighting and complex architecture [22]. The technique uses a threshold vector in conjunction with GPSO and EKFC to calculate and regulate the optimal number of clusters. The algorithm solves the clustering problem using an iterative fuzzy partitioning technique. The recommended system-based CNN model performs better than LSTM, decreasing false positives and achieving 97% accuracy.

## 3. Proposed HPSO-T Technique

This section presents the suggested HPSO-T. The suggested approach avoids local optimum limitations and gives the swarm superior prospecting and extraction capabilities by including PSO and thresholding techniques. Sophisticated optimization problems are solved by using the predatory behavior of swarms. Nevertheless, the PSO algorithm is used to find the ideal solution, giving Swarm an improved balance of discovery and extraction. Thus, in the picture thresholding technique, the HPSO-T algorithm performs better. The histogram's data is typically used to determine thresholding, and the distinct valley of the histogram contains the ideal thresholds. However, because the histogram includes large, distinct peaks and troughs, determining this ideal threshold is difficult and complicated. The time required to compute for picture thresholding grows significantly with the threshold amount.

The issue of thresholding images can be solved in several ways, such as using computational evolutionary algorithms to cut down on the time required for processing. PSO is effectively used in picture thresholding because of its superior effectiveness in identifying the best alternative while tackling multimodal problems with optimization. Self-parallel evolutionary approaches, or PSOs, effectively resolve many optimization issues. But it has its drawbacks, like most algorithms developed over time. For instance, the solution found using the PSO algorithm can be a regional preferred approach rather than an optimal global one if the issue has numerous localized extrema. Our approach involves adding a specific stochastic perturbation to every single component after the traditional PSO technique's execution to enhance the diversity of populations and prevent early convergence or slipping into regional catastrophic holds of the algorithm. This is done to minimize the occurrence of this type of phenomenon.

Optimum thresholds are used to split the picture into two parts during the bi-level thresholding of the imaging procedure. The threshold is used to achieve exact picture separation because, as thresholds rise, splitting one image into several parts becomes more difficult.

Finding the ideal value of the threshold for the segmentation of images is the main goal of image thresholding. Equation (1) provides a mathematical formulation for segmenting image I with m+1 class using m optimum threshold values.

$$m = \{g(x, y) \in I|\ 0 \leq g(x, y) \leq t - 1\} \tag{1}$$

Hence, for picture I, the threshold values are indicated by the symbol t. A pixel's grey level value is denoted as g(x, y), while L denotes the gray level number. The estimated likelihood of a gray level (Pi) is expressed as equation (2) if the levels of gray are thought to be in the range of 0 to L-1.

$$P_i = h(i)|N, \text{ for } i=0,1, 2, \ldots L-1 \tag{2}$$

The overall quantity of pixels in the image is expressed as N, whereas the aggregate number of pixels in the gray level is indicated as h (i). Equations (3), (4), and (5) can be used to calculate the mean class values (μm), mean total value (μt), and class occurrence probability (ωm) in the instance in which there is m threshold (t1, t2,... tm) that split the level of the gray image into m+1 class.

$$\text{Class mean } \mu_m = \sum_{i=t_m}^{t_{m+1}-1} \frac{iP_i}{\omega_i} \tag{3}$$

$$\text{Class occurrence probability } \omega_m = \sum_{i=t_m}^{t_{m+1}-1} P_i \tag{4}$$

$$\text{Total mean value } \mu_T = \sum_{i=0}^{L-1} iPi \tag{5}$$

Equation (6) is the goal functionality for multiple levels of thresholding derived from the mean class, probability of occurrence, and cumulative mean values.

$$f = \sum_{m=0}^{M} \omega_m (\mu_m - \mu_T)^2 \tag{6}$$

Where $\mu_m$ denotes the class mean,  denotes the total mean, and indicates the class occurrence probabilities. The desired function is optimized, and the best multilevel thresholding solution is found using the suggested hybrid optimization approach. An overview of the suggested HPSO-T method procedure is shown in Figure 1.

This algorithm's main focus is that new particles deal with the current best location in the neighborhood. The existing canonical PSO algorithm cycles through equations (7) and (8), one determining the particle's position and the other determining its velocity.

$$u_i = wu_i(t) + a_1r_1\big(P_i - y(t)\big) + a_2r_2\left(P_g - y_i(t)\right) \quad (7)$$

$$y_i\,(t+1) = y_i(t) + u(t) \quad (8)$$

Where $u_i$ (t) and $y_i$ (t) are vectors indicating the present location and velocity correspondingly, $0 \leq W < 1$ is a weight of inertia that controls the amount of the initial velocity particle that is retained and $a_1$, $a_2$ are two variables of constructive velocity, $r_1$, $r_2$ are two identical combinations of random events were taken from U (0,1), $P_i$indicates the best point of the particle, initiated by the $i^{th}$ particle, and$P_g$representing its finest location so far, which was discovered by the entire swarm.

Equation (9) can be created by combining the updated equations (7) and (8), assuming we equal zero.

$$y_i(t+1) = y_i(t) + a_1r_1\big(P_i - y_i(t)\big) + a_2r_2\left(P_g - y_i(t)\right) \quad (9)$$

The local search capability increases, while this formula decreases the global search capability. So, if $y_j$ (t) = $P_j$= $P_g$, particle j at the velocity zero. In order to increase the swarm's $P_g$ current best position, we conserve it. Also, the particle j's position (t + 1) is arbitrarily initialized, and the other particles are modified in accordance with equation (4), which results in equation (10).

$$P_j = y_j(t+1) \quad (10)$$

If $P_j = P_g$, then the particle j's position $y_j$ (t + 1) must continue to randomly initialize and manage additional particles in accordance with (9); if $P_j = P_g$, and remains constant, all particles are controlled in accordance with (9); if$P_j = P_g$, and changes $p_g$, an integer k1j exists, which is satisfied using $y_k$ (t + 1)= $P_k$= $P_g$, therefore, in accordance with equation (9), the position of particle k represents $y_k$ (t) must continue to be initialized arbitrarily, and other particles are changed, thus improving search capability.

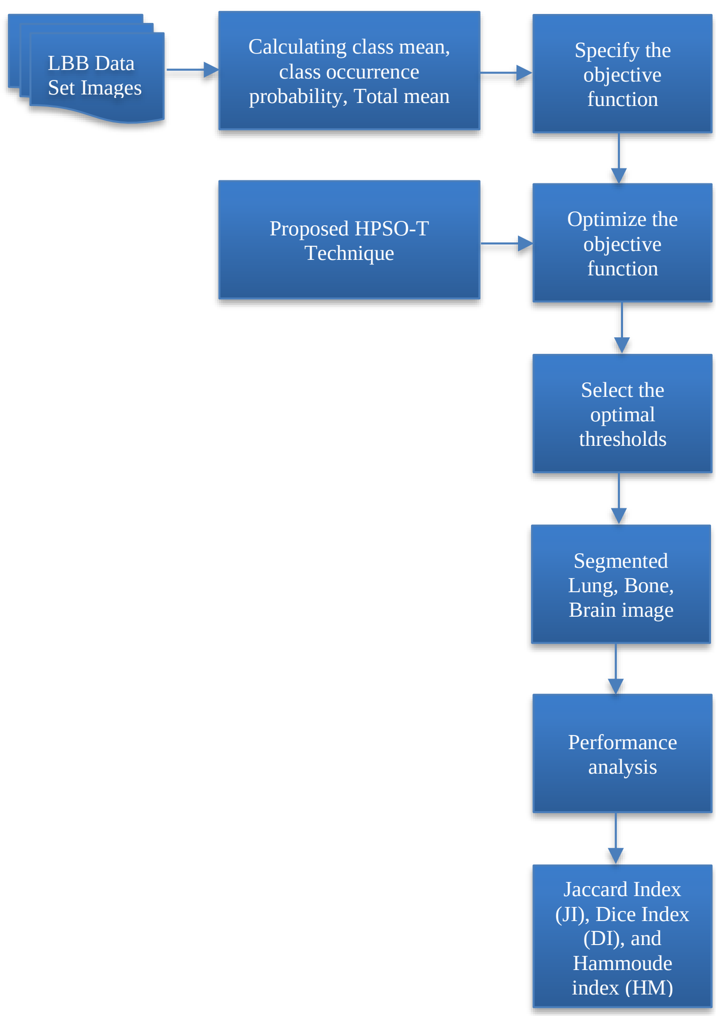



**Fig. 1 The proposed HPSO-T technique process**

The likelihood of a certain number of pixels matching a given gray value occurring is:

$$P_i = S_i / S$$

Step : 1 The image is to be divided and pre-processed.
Step : 2 Set the parameters, initialize the threshold group coordinates, and produce the initial speed at random.
Step : 3 Specify the number of dimensions D and the swarm size S.
Step : 4 Every particle i in the [1..S]
Step : 5 Create Xi and Vi at random, then calculate Xi's fitness and indicate it as f (Xi).
Step : 6 Set Pb = Xi and f (Pb) = f (Xi)
Step : 7 if f (Pb) < f (Gb), then
Step : 8 f (Gb) = f (Pb)
Step : 9 end if
Step : 10 while t < maximum number of iterations
Step : 11 for each particle i∈ [1..S]
Step : 12 Evaluate its velocity vid (t + 1) using Equation (9)
Step : 13 Update the position xid (t + 1) of the particle using Equation (10)

## 4. Results and Discussion

The proposed approach was validated, and its functionality and results were tested using a series of simulated evaluation studies. The datasets that were used were obtained from the Kaggle website. Both normal and pathological LBB images were included in the data sets used in this investigation. MATLAB has built-in tools for image processing, so it is essential to use them in all simulated scenarios. The original LBBMRI image, the segmented LBB MRI image using HPSO-T, is shown in Table 1.

The performance of the segmentation method is determined by comparing the proposed HPSO-T segmentation image with PSO segmentation methods and thresholding segmentation methods based on ground (gold) truth image using the Jaccard Index (JI), Dice Index (DI), and Hammoude Index (HM) to estimate how well the methods of segmentation performed.

### *4.1. Jaccard Index (JI)*

The Jaccard Index (JI) is a statistic used to assess how similar and diverse two data frames are. The data windows Xi and Xj should be considered. The coefficient, which evaluates the level of overlap between the two windows, is calculated from the ratio of common qualities between windows Xi and Xj. For simplicity, disregard data windows in favour of two sets, A and B. Set theory allows us to quantify the region of intersection (A ∩ B) and union (A ∪ B) between these two sets. As a result, equation 11 uses the following formula to determine the Jaccard index.

$$\text{Jaccard(A,B)}=\frac{A \cap B}{A \cup B} \tag{11}$$

### *4.2. Dice Index (DI)*

Equation 12 defines the conventional Dice coefficient.

$$\text{DI}=\frac{2\,|A \cap B|}{|A|+|B|} \tag{12}$$

Here, A is a set reflecting the actual data, and B is the generated segmentation. Each voxel in both images (sets) has a binary value of '0' or '1'. (or pixels in the 2D case). Here, a and b are used to represent these values, respectively.

### *4.3. Hammoude Index (HM)*

It makes a pixel-by-pixel comparison enclosed by the two boundaries defined in equation 13.

$$\text{HM(A,B)}=\frac{(A \cup B)-(A \cap B)}{(A \cup B)} \tag{13}$$

Table 2 compares normalized mean values based on validating parameters for the proposed HPSO-T algorithm with the existing PSO and thresholding algorithm. The JI and DI values are greater (closer to one) as the split picture profile approaches the gold-colored reference imaging contour. When the HI is low (close to zero), the segmented picture contour closely resembles a gold-colored standard imaging contours.

**Table 2. Validating parameters for proposed GPSO-EKFC with existing methods**

| Segmentation algorithm | JI | DI | HI |
|---|---|---|---|
| Proposed HPSO-T algorithm | 0.85 | 0.91 | 0.19 |
| PSO algorithm | 0.81 | 0.9 | 0.22 |
| Thresholding algorithm | 0.87 | 0.93 | 0.14 |

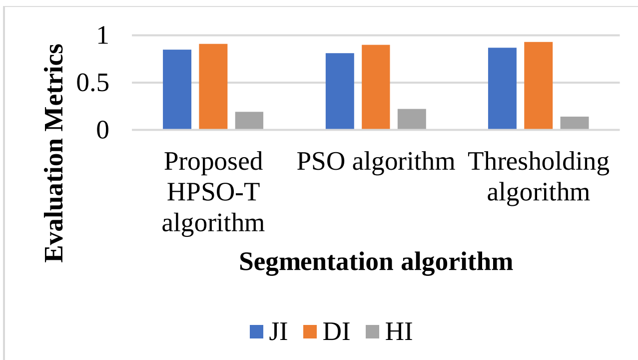



**Fig. 2 Comparison of the proposed algorithm's performance evaluation metrics with those of the current algorithm**

Figure 2 shows the comparable outcomes of the performance evaluation metrics of the suggested HPSO-T, PSO and thresholding algorithm. According to the outcomes, the proposed HPSO-T segmentation approach outperforms the other two methods.

The comparative results with respect to the above-said methods are shown in Table 3. The graphical comparative analysis between the used and existing methods is shown in Figure 3.

**Table 3. Comparative analysis of the accuracy of the projected method with various methods**

| Various Methods | Accuracy |
|---|---|
| PSO, GA, and SVM algorithms [23] | 89.5 |
| K-NN classification using GA[24] | 90 |
| Proposed HPSO-T Method | 95.81 |

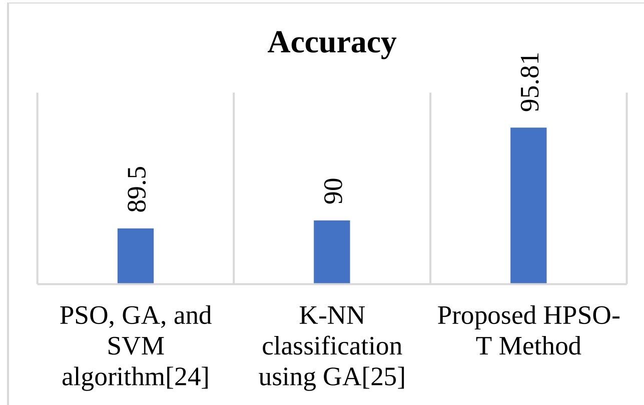
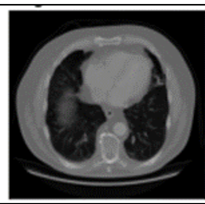
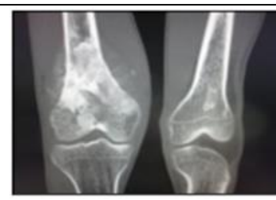
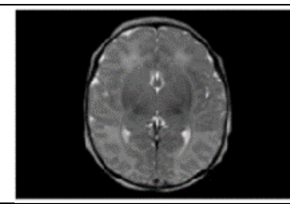
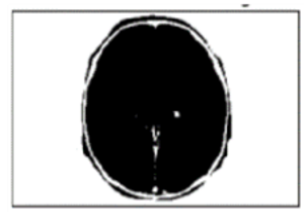
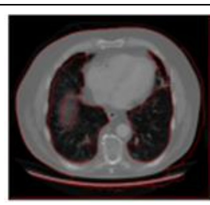
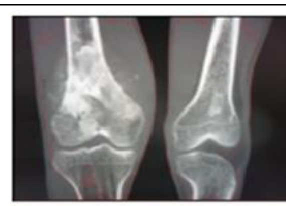
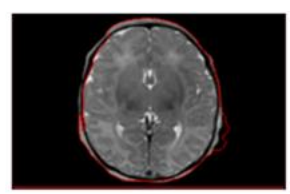



**Fig. 3 Comparison of the proposed algorithm's accuracy with the existing algorithm**

**Table 1. LBB MRI image, the segmented image of LBB MRI using HPSO-T**

| | **Lungs** | **Bone** | **Brain** |
|---|---|---|---|
| **Input image** |  |  |  |
| **After Thresholding** |  |  |  |
| **Grayed Image** |  |  |  |
| **Segmented Image** |  |  |  |

## 5. Conclusion

A HPSO-T algorithm for thresholding is presented in this research work. Here, we analyse and segment data from various MRI images of the Lung, Brain, and Bone tumour. The comparison of normalized mean values is based on validating parameters for the proposed HPSO-T algorithm with the existing PSO and thresholding algorithm. This framework for medical image segmentation with a thresholding group coordinates the attribute score calculation, and the results are obtained. In the future, specific optimization could be suggested to increase the dimensionality and accuracy of segmentation.

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