Computational intelligence optimization approach based on particle swarm optimizer and neutrosophic set for abdominal CT liver tumor segmentation

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ABSTRACT

In this paper, an improved segmentation approach for abdominal CT liver tumor based on neutrosophic sets (*NS*), particle swarm optimization (PSO), and fast fuzzy C-mean algorithm (FFCM) is proposed. To increase the contrast of the CT liver image, the intensity values and high frequencies of the original images were removed and adjusted firstly using median filter approach. It is followed by transforming the abdominal CT image to *NS* domain, which is described using three subsets namely; percentage of truth *T*, percentage of falsity *F*, and percentage of indeterminacy *I*. The entropy is used to evaluate indeterminacy in *NS* domain. Then, the *NS* image is passed to optimized FFCM using PSO to enhance, optimize clusters results and segment liver from abdominal CT. Then, these segmented livers passed to PSOFCM technique to cluster and segment tumors. The experimental results obtained based on the analysis of variance (ANOVA) technique, Jaccard Index and Dice Coefficient measures show that, the overall accuracy offered by neutrosophic sets is accurate, less time consuming and less sensitive to noise and performs well on non-uniform CT images.

1. Introduction

Segmentation is a critical and essential process and is one of the most difficult tasks in image processing. Automatic segmentation of CT liver tumor is a very challenging task, due to various factors, such as the low-level contrast and blurry edged images, irregularity in the liver shape and size between the patients and the similarity with other organs of almost same intensity like spleen and stomach. Also, liver parenchyma is stretched over 150 slices in a CT image and different from patients, indefinite shape of the lesions and low intensity contrast between lesions and similar to those of nearby tissues make automatic liver and lesions segmentation difficult [1,2]. Among various image segmentation techniques, traditional segmentation methods have certain drawbacks, which cannot be used for accurate result and time computation.

Fuzzy theory has been applied to image segmentation, which retains more information than that of the hard segmentation methods. Fuzzy C-means (FCM) is a fuzzy clustering method allowing a piece of data to belong to two or more clusters. The FCM algorithm obtains segmentation results by using fuzzy classification [3]. In some applications such as CAD systems, we should consider not only the truth and falsity membership, but also we want the indeterminacy membership. It is hard for classical fuzzy set to solve such problems [3,4]. As a generalization of fuzzy logic, neutrosophic logic introduces a percentage of 'indeterminacy' due to unexpected parameters hidden in some propositions and carries more information than fuzzy logic [5].

Many problems in medical images have been solved by considering bio-inspired meta-heuristic optimization algorithms such as Social Spider Optimization (SSO), Ant Colony Optimization (ACO), Crow Search Optimization (CSO), and particle swarm optimization (PSO). Computational bio-inspired algorithms have been used in situations where conventional techniques cannot find a satisfactory solution or they take too much time to find the solution [42]. Therefore, this paper introduces a very powerful optimization method, both in terms of speed and optimal convergence, which can be con-

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sidered for a wide variety of segmentation problems in medical images.

In this paper, we present an automatic liver tumor segmentation approach based on neutrosohic sets (*NS*), fast fuzzy c-means clustering algorithm (FFCM) and particle swarm optimization algorithm (PSO). To increase the contrast of the CT liver images median filter approach is used to adapt intensity values and remove high frequencies from the original images. It is followed by transforming the abdominal CT image to *NS* domain which is described by using *T*, *I*, and *F* components. The entropy is used to measure and evaluate the indeterminacy in *NS* domain. Then the *NS* image is passed to FFCM clustering algorithm guided by PSO to enhance, optimize cluster results and segment abdominal CT image in less time consuming with high accuracy. To demonstrate the performance of this new approach, a methodical and statistical comparisons with two other techniques for CT image segmentation are carried out.

The remainder of this paper is organized as follows. Section 2 discusses the related works. Section 3 recalls some preliminaries of the fuzzy c-means, particle swarm optimization and neutrosophic sets that are relevant to this paper. The hybrid proposed *NS*-PSOFFCM approach is discussed in Section 4. Experimental results and analysis with details are discussed in Section 5. Finally, conclusion and future work are discussed in Section 6.

2. Related work

Many algorithms and several researches have been proposed to address the problems of image segmentation in general and in medical imaging in particulars. For example, Siri and Latte [6], proposed a new fuzzy C-means algorithm (α-FCM) to segment the image on *NS* domain. The experimental results demonstrate that the proposed approach can segment the images automatically and effectively, but it is very time consuming. Also, Cheng et al. [7], proposed a novel segmentation approach based on neutrosophic theory and modified fuzzy clustering approach. Zhang [8], applied watershed segmentation based on neutrosophic sets to image segmentation and represent the objects as *T* and background as *F*. The blurry edges are gradually changed from objects to background, and there are no clear boundaries between the objects and edges or between the background and edges. The blurry boundaries are defined as *I*. This approach is good for handling a uniform background and objects with blurry edges. Anter et al. [3], improved liver segmentation using neutrosophic sets and FCM. The liver CT images are transformed to *NS* domain. Then the adapted threshold is used using three classes FCM clustering algorithm.

Many problems in abdominal CT images have been solved by considering bio-inspired meta-heuristic optimization algorithm. The main drawbacks of FCM which are the number of clusters needs to be predefined and the results is dependent on the initial selection of the centroids. FCM known to present very slow convergence on hard problems, such as gray-scale CT images. To overcome this shortcoming of FCM, FCM can be guided by computational meta-heuristics algorithms such as PSO algorithm. Alam et al. [9], proposed a hybridized clustering approach for image segmentation using PSO to improve the classical FCM algorithm. The results show that the hybridized clustering approach can provide better effectiveness on image segmentation.

Jing and Bo [10] proposed a fast FCM method together with PSO for image segmentation. The PSO algorithm is an optimization process which automatically determines the number of clusters as well as the center of the clusters. Venkatesan and Parthiban [11] proposed fuzzy C-means and maximum entropy optimized by PSO to segment and detect abnormalities present in the image. The analysis is carried out by comparing the segmentation results and intra/inter cluster distances. Different types of noise has been added

to the original image to test the robustness of FCMPSO. The FCMPSO gives accurate results and less time consuming. Hongpo et al. [12] proposed hybrid algorithm using PSO incorporated with FCM algorithm (PSOFCM) to segment sonar images. The results show that the PSOFCM is better than FCM in sonar segmentation images.

Many researchers applied multilevel Otsu threshold using PSO for image segmentation for example, Sathya and Kayalvizhi [13], proposed a multilevel thresholding method based on PSO and compared their method with genetic algorithm (GA) based threshold. The experimental results show that the PSO executed faster and more stable than GA and less parameters than GA. However, a general problem with the PSO and other optimization algorithms is that of becoming trapped in a local optimum, such that it may work in some problems but may fail on others. For this reason researcher tried to select best parameters for PSO to get high accuracy. Ates et al. [43] applied Darwin PSO (DPSO) with multi-level threshold for improving segmentation accuracy but still has problems in time computation.

Chander et al. [44] proposed a new variant of PSO with adapting 'social' and 'momentum' components for image segmentation using optimal multi-level thresholding. The proposed system used iterative scheme to obtain initial values of candidate multilevel thresholds

Zhang et al. [14] illustrated how possibility C-means algorithm (PCM) can be integrated with PSO and provide a significant improvement on the efficiency of the segmentation. The PCM is more accurate as compared to FCM, as it overcomes the relative membership problem of FCM in image segmentation, and has shown good performance in the presence of severe noise and outliers. Experimental results show that the proposed algorithm has a significant improvement on the effect and efficiency of segmentation comparing with the standard FCM clustering algorithm.

Gopal and Karnan [15], proposed an intelligent system to diagnose brain tumor through magnetic resonance imaging (MRI) using FCM clustering algorithm along with intelligent optimization algorithm genetic algorithm (GA), and PSO. The detection of tumor is performed in two phases. In first phase pre-processing and enhancement are applied to remove labels and X-ray marks and to remove high frequency components using median filter. The FCM calculates the adaptive threshold and PSO automatically select initial cluster seed point. Hammouche et al. [16], illustrated that PSO based segmentation is accurate and better than other methods such as GA, ant colony optimization (ACO), differential evaluation (DE), and simulated annealing (SA) in terms of precision, robustness of the results, and running time. Mitra et al. [17], illustrated that the PSO better than GA in terms of time consuming in CPU and fitness value.

Raju and Rao [18] proposed FCM algorithm integrated with PSO for segmenting mammography images. The experimental analysis and performance shows that, FCM along with PSO gives better performance and good accuracy, as compared to other techniques. The computational complexity is largely reduced using the proposed algorithm for image segmentation. Deepa [19] used the FCM clustering algorithm for segmentation which is further enhanced by using PSO algorithm. The proposed FCM clustering algorithm for segmentation and PSO for clear identification of clusters in mammogram images. The result indicates that this system can facilitate the doctors to detect breast cancer in the early stage of diagnosis process. Ozturk et al. [20] presented a dynamic clustering based on PSO (DCPSO). The experimental results show that, the proposed approach automatically determines the optimum number of clusters using binary PSO. Then the centers of the selected clusters are refined by K-means algorithm.

Therefore, the implementing *NS* approach to the segmentation process for CT images may allow achieving both vital and important goals at once. As a result, it is easy to detect that PSO-based

Table 1
List of symbols.

Algorithm	Symbol	Description
FFCM	μ	Membership function
	O_j	Object
	c_i	Centroids
	m	Fuzzifier or weight index
	$d_{i,j}$	Euclidean distance
PSO	r_1 and r_2	Random variables between [0, 1]
	ρ_1 and ρ_2	Personal and cognitive coefficient
	W	Inertial weight between[0, 1]
	X_n	Position at iteration n
	V_n	Velocity at iteration n
Neutrosophic set	$T(i, j), I(i, j), F(i, j)$	True, indeterminate, and false neutrosophic image
	P_{NS}	Image transformation to neutrosophic domain
	NS	Neutrosophic set
	$g(\bar{i}, j)$	Local mean value
	g_{max} and g_{min}	Peaks greater than mean of local maxima
	Ho	Homogeneity value
	En	Image entropy

segmentation methods are considered an efficient way in terms of convergence speed, precision, robustness of the results and running time.

3. Preliminaries

This section provides a brief explanation of the methods and algorithms used in this paper for CT liver tumor segmentation, the FCM algorithm, PSO and neutrosophic sets, along with some of the key basic concepts. A more comprehensive review can be found in [3,18,21,22].

3.1. Fuzzy C-means clustering algorithm (FCM)

FCM is an unsupervised learning and a very common technique for statistical data analysis used in many fields, due to its overall performance. Data point in FCM can belong to all classes with different degrees of membership. FCM adopts fuzzy partitions of given data between 0 and 1 [23].

Let O be the set of n data elements, and C be the set of c centroids. The FCM partitions O into c clusters by minimizing the following objective function [16]:

$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} \left(\mu_{ij}\right)^m \left\| o_j - c_i \right\|^2 \qquad (1)$$

where $1 \leq m \leq \infty$ is the *fuzzifier*, c_i is the ith centroid corresponding to cluster β_i, $\mu_{ij} \in [0, 1]$ is the fuzzy membership of the pattern o_j to cluster β_i, and $\|.\|$ is the distance norm (see Table 1). The centroids and membership function can be updated using Eqs. (2) and (3):

$$c_i = \frac{1}{n_i} \sum_{j=1}^{n} \left(\mu_{ij}\right)^m o_j \quad where \quad n_i = \sum_{j=1}^{n} \left(\mu_{ij}\right)^m \qquad (2)$$

$$\mu_{ij} = \frac{1}{\displaystyle\sum_{k=1}^{c} \left(d_{ij}/d_{kj}\right)^{2/(m-1)}} \quad where \quad d_{ij}^2 = \left\| o_j - c_i \right\|^2. \qquad (3)$$

In order to segment N-dimensional CT liver gray-scale image into C classes using a memory efficient implementation of the fuzzy C-means clustering algorithm called fast fuzzy C-means (FFCM). The computational efficiency is achieved by using the histogram of the image intensities during the clustering process instead of the raw image data. For more details in [24].

3.2. Swarm model based particle swarm optimization (PSO)

PSO is an artificial intelligence technique that can be used to find approximate solutions to extremely difficult or impossible numeric maximization and minimization problems [25].

PSO was firstly introduced by Kennedy and Eberhart [26], as a stochastic optimization technique that simulates the behavior of a flock of birds for searching where the food is. The PSO algorithm has many advantages. It shares many similarities with evolutionary computation such as GA. PSO is based on random populations and searches for optima by updating generations. PSO has no operators such as crossover and mutation as in GA and finally, PSO can be used to handle and balance exploration and exploitation [27]. The details operation of PSO are given below:

The velocity and position of all particles are randomly set to within predefined ranges. The fitness function represented by Eq. (1) is used to evaluate the particles success. To model the swarm, each particle moves in a multidimensional space according to the position $x_n[t]$, and velocity $v_n[t]$, which are highly dependent on local best $\breve{x}_n[t]$ and global best $\breve{g}_n[t]$ information:

$$\left\{ v_n[t+1] = w v_n[t] + \rho_1 r_1 (\breve{g}_n - x_n) + \rho_2 r_2 (\breve{x}_n - x_n[t]) \right. \qquad (4)$$

$$x_n[t+1] = x_n[t] + v_n[t+1] \qquad (5)$$

Coefficients ρ_1 and ρ_2 are assigned weights, which control the inertial influence of *the globally best* and *the locally best*, respectively, when the new velocity is determined. Detailed description of all symbols are given in Table 1.

The parameter w, commonly known as inertial coefficient that is used to determine a new velocity and has range $0 < w < 1$. With a small w, particles ignore their previous activities, thus ignoring the system dynamics and being susceptible to get stuck in local solutions (exploitation behavior). On the other hand, with a large w, particles will present a more diversified behavior, which allows exploration of new solutions and improves the long-term performance (exploration behavior).

The parameters r_1 and r_2 are random vectors with each component generally a uniform random number between 0 and 1. It is noteworthy that the velocity dimension, i.e., $dimv_n[t]$, as well as the position dimension, i.e., $dimx_n[t]$, correspond to the total number of desired cluster centers of the image.

Cluster analysis is concerned with the division of objects (data vectors) into subsets, such that each subset is as homogeneous as possible, while each subset should differ as much as possible from other subsets. The main drawbacks of Fuzzy c-means are that the number of clusters needs to be specified beforehand, and that the result is dependent on the initial selection of the centroids. There is again no guarantee that it will converge to the global optimum.

The utilization of PSO for clustering data has not been researched much. Das et al. [28] proposed PSO to fuzzy clustering for clustering image pixels as an alternative to conventional partitioned clustering algorithms (for example, based on evolutionary algorithms, or non-PSO adaptations). According to this paper, applying PSO to fuzzy clustering as new approach. Each particle must represent a possible solution to the problem. PSO can be used as a method for clustering by letting each particle represent cluster centroids. An important advantage of using PSO over traditional clustering algorithms is that it can maintain, recombine and compare several candidate solutions simultaneously. Therefore, PSO can overcome local optima problem. In contrast, FCM clustering algorithm always will converge to the local optimum that is the closest to the starting point of the search.
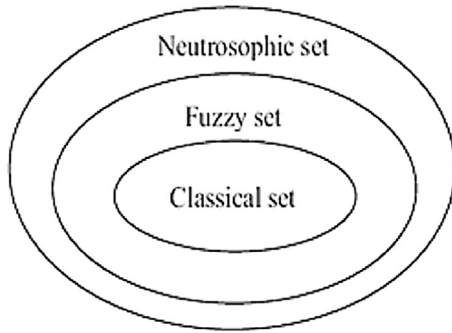
Fig. 1. Relationships among neutrosophic set and other sets.

3.3. Neutrosophic sets

Neutrosophy is a branch of philosophy, it is a generalization of an intuitionistic set, fuzzy set, para-consistent set, dialetheist set, paradoxist set, and a tautological set. neutrosophic set and its properties are discussed briefly in [1,29]. The problems which cannot be solved by fuzzy logic can be tackled by neutrosophic logic. This is mainly because *NS* introduces new component called indeterminacy and studies the neutrosophic logical values of the propositions that represented by (*T*, *I*, and *F*) [30].

Definition 1 (*Neutrosophic set*). Let *T*, *I*, and *F* as neutrosophic components. Let *T*, *I*, and *F* be standard or non-standard real subsets of]⁻0, 1⁺[. An element *A*(*T*, *I*, *F*) belongs to the set in the following way: it is *t* true (*t* ∈ *T*), *i* indeterminate (*i* ∈ *I*), and *f* false (*f* ∈ *F*), where *t*, *i*, and *f* are real numbers [31,32].

In order to apply neutrosophy, an image needs to be transferred to a neutrosophic domain P_{NS} [31]. A pixel in the neutrosophic domain can be represented as *T*, *I*, and *F* meaning the pixel is *t*% true, *i*% indeterminate, and *f*% false, where *t* varies in *T*, *i* varies in

I, and *f* varies in *F*, respectively. In a neutrosophic set, $0 \le t, i, f \le 1$. However, in a classical set, $i = 0$, *t* and *f* are either 0 or 1 and in a fuzzy set, $i = 0, 0 \le t, f \le 1$ [33]. Fig. 1 shows the relationship between a neutrosophic set and other sets.

$T(i,j), I(i,j), F(i,j)$ is the neutrosophic set components, each pixel $P(i,j)$ in image domain transformed to *NS* domain $P_{NS}(i,j)$ which are calculated as follows:

$$P_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\} \tag{6}$$

$$T(i,j) = \frac{g(\bar{i},j) - \bar{g}_{\min}}{\bar{g}_{\max} - \bar{g}_{\min}} \tag{7}$$

$$I(i,j) = 1 - \frac{Ho(i,j) - \bar{Ho}_{\min}}{\bar{Ho}_{\max} - \bar{Ho}_{\min}} \tag{8}$$

$$F(i,j) = 1 - T(i,j) \tag{9}$$

$$Ho(i,j) = abs(g(i,j) - g(\bar{i},j)) \tag{10}$$

where $g(\bar{i},j)$ is the local mean value of the window size, and $Ho(i,j)$ is the homogeneity value (see Table 1).

Definition 2 (*Neutrosophy image entropy*). Image entropy is defined by summation of the three subsets entropies *I*, *F*, and *T* [32]. If entropy is maximum, the different intensities have equal probability and the intensities distribute uniformly. If the entropy is small, the intensities have different probabilities and their distributions are non-uniform.

$$En_T = -\sum P_T(i) \ln P_T(i) \tag{11}$$

$$En_F = -\sum P_F(i) \ln P_F(i) \tag{12}$$

$$En_I = -\sum P_I(i) \ln P_I(i) \tag{13}$$
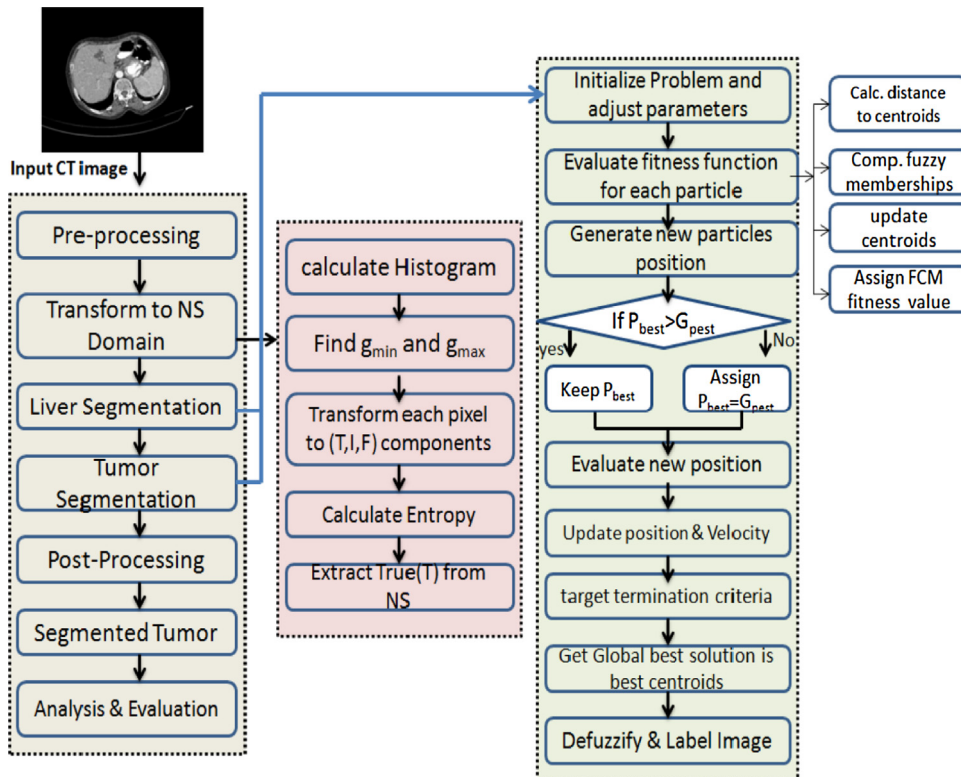
$$En_{NS} = En_T + En_I + En_F \tag{14}$$

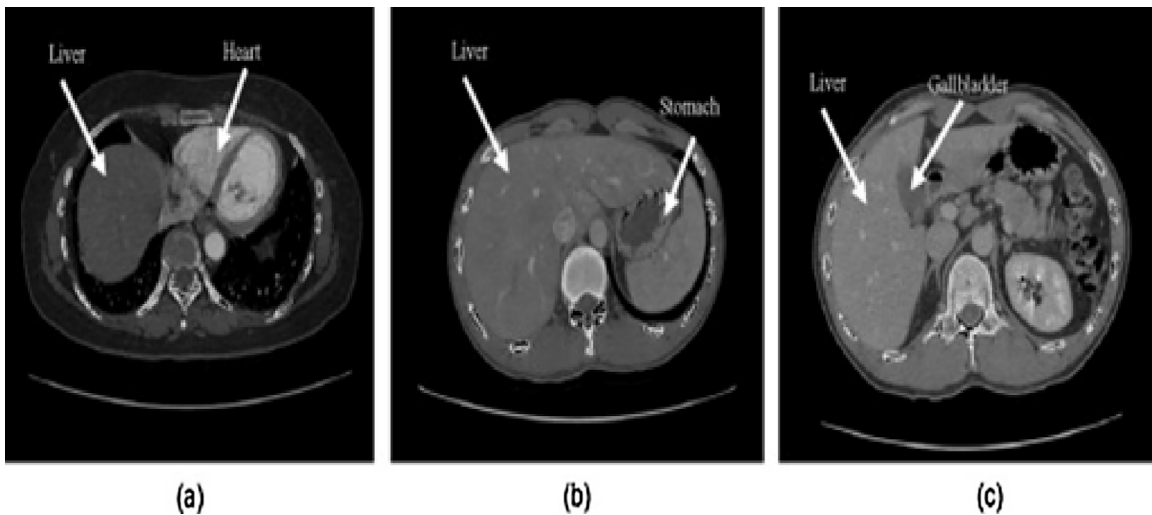**Fig. 2.** The proposed NS-PSOFFCM approach.

Fig. 3. In abdomen region, there are several limbs that are in contact with liver, (a) liver and heart are very closed, (b) liver and stomach, and (c) liver and gallbladder are very closed and have the same intensity.
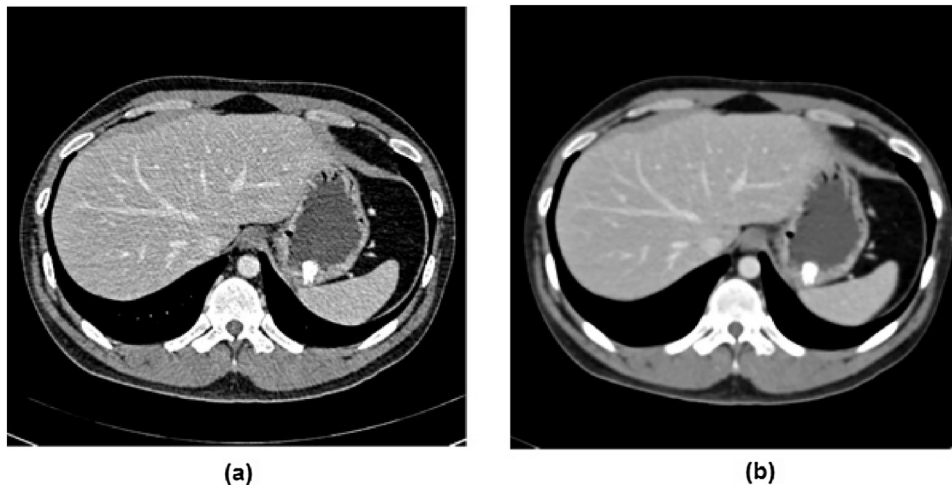

Fig. 4. CT liver enhancement using median filter approach. (a) The original image. (b) Enhanced CT image.

where En_I, En_T and En_F are the entropy of subsets T, I and F, respectively. $P_T(i)$, $P_F(i)$, and $P_I(i)$ are the probabilities of element i in T, I and F. En_I is employed to evaluate distribution of indeterminacy, and En_T and En_F are utilized to measure the distribution of the elements in NS.

4. The proposed NS-PSOFFCM segmentation approach

In general, the hybrid neutrosohic set, bio-inspired PSO and fast FCM (NS-PSOFFCM) approach introduced in this paper is composed of four phases, namely;

- **CT liver image enhancement** by applying a median filter approach to enhance and remove high frequencies of the original CT liver images.
- **Transform to NS domain** by transforming the enhanced CT liver images to neutrosohic domain.
- **CT liver parenchyma and tumor segmentation** by applying a fast FCM algorithm guided by Bio-Inspired PSO optimization to optimize the cluster centers.
- **Analysis and evaluation: Evaluation criteria** analysis of variance (ANOVA) technique, Jaccard Index and Dice Coefficient

measures, show that the overall accuracy offered by the employed proposed hybrid NS-PSOFFCM approach.

These four phases are described in details in this section along with the steps involved and the characteristics feature for each phase. Fig. 2 shows the overall layout of the proposed NS-PSOFFCM approach based on optimized FFCM clustering using bio-inspired PSO for improving liver CT image segmentation.

4.1. CT liver image enhancement: median filter approach

In this paper, an effective median filtering was evaluated and analyzed to remove high frequency components, smooth CT image and increase the efficiency of the proposed approach.

4.2. Transform CT liver image to NS domain

The steps of the proposed Neutrosophic logic approach is illustrated in Algorithm 1. The image is transformed to NS domain based on T, I and F and entropy is used to evaluate and measure the degree of indeterminacy in this NS image. Then, the true objects in NS image becomes more uniform and homogeneous, and more suitable for segmentation process.
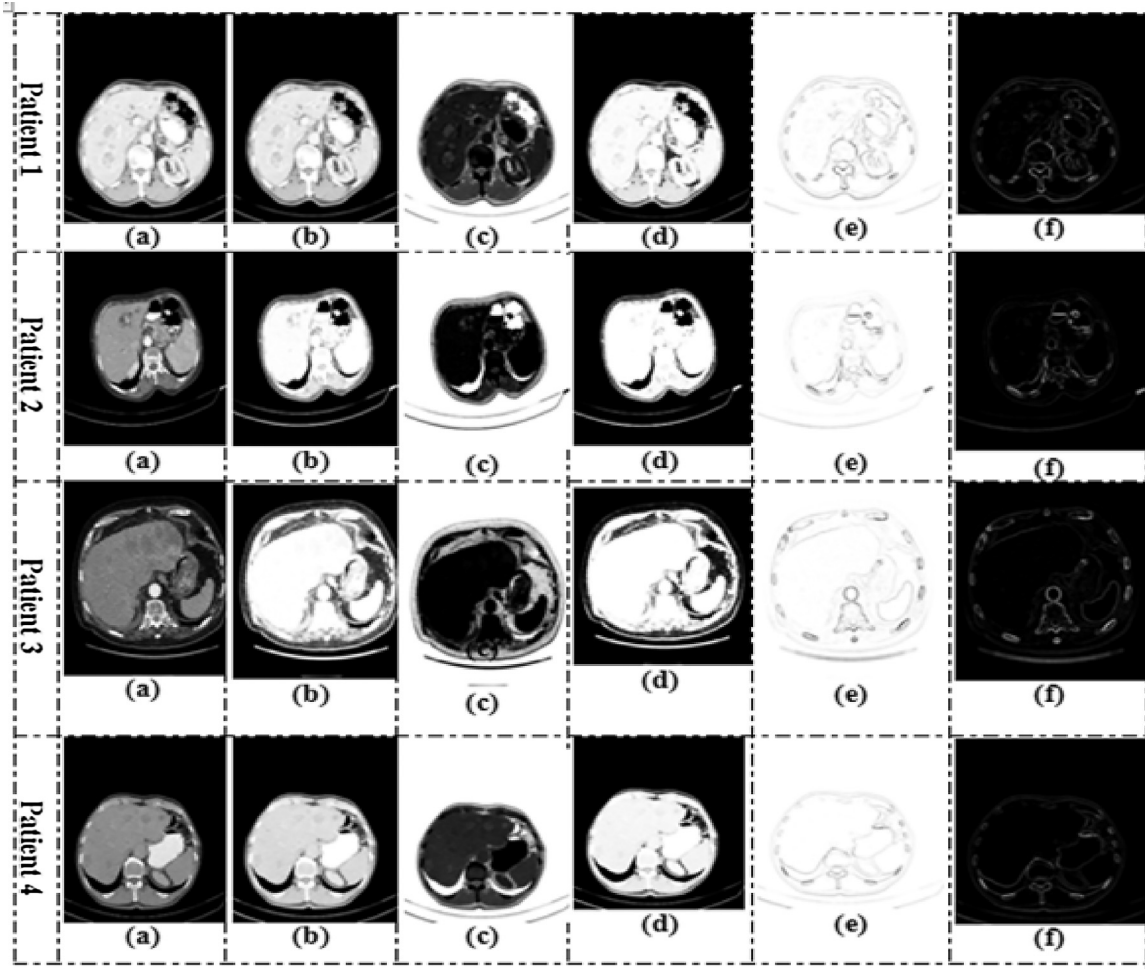
Fig. 5. The results obtained from the proposed *NS* approach on different slice's: (a) original image, (b) true domain image, (c) False domain image, (d) enhanced *NS* image, (e) homogeneity image, (f) indeterminate image.

Algorithm 1. Neutrosophic logic approach

1: Convert each pixel of image to *NS* domain.
2: Calculate local maximum of histogram $g(i, j)$ and find first peak $\bar{Ho}_{min}$ and last peak $\bar{Ho}_{max}$ greater than local mean.
3: $T(i, j)$ domain is calculated from Eq. (7).
4: $I(i, j)$ domain is calculated from Eq. (8).
5: $F(i, j)$ domain is calculated from Eq. (9).
6: Apply entropy En_{NS} to evaluate the indeterminacy in *T*, *I*, and *F*.

4.3. CT liver parenchyma and tumor segmentation: PSOFFCM approach

After the CT image is transformed to *NS* domain, the indeterminacy can be increased and noise can be removed hence CT image becomes homogeneous, and suitable for clustering. The FFCM is optimized by bio-inspired PSO to improve the performance, accuracy and reduce time computation in clustering process. At each step, the particles are manipulated and p_{best} and g_{best} locations are identified for iteration *t* according to Eqs. (4) and (5). Each particle represent a possible solution to the problem. An important advantage of using PSO over traditional clustering algorithms is that it can maintain, recombine and compare several candidate solutions simultaneously. Therefore, PSO is good at coping with local optima. Algorithm 2 shows the main steps of the proposed PSOF-FCM approach. After CT image is clustered morphological operators and Connected Component Labeling algorithm are applied to segment liver parenchyma from abdominal CT. Then PSOFFCM is iteratively applied to cluster the segmented Liver parenchyma to detect liver tumors.

Algorithm 2. The proposed PSOFFCM clustering approach

1: Initialize w, ρ_1, ρ_2
2: Initialize N //number of particles
3: Initialize I_T //total number of iterations
4: Initialize c //no. of clusters
5: Initialize $[0 \quad \cdots \quad 0]^T \leq x_n[0] \leq (L-1) \times [1 \quad \cdots \quad 1]^T$ randomly initialize the cluster centroids, i.e., position of particles
6: Initialize $\breve{x}_n$, $\breve{g}_n$ based on $x_n[0]$ initial local and global best positions
7: Initialize J_n^{best}, J_T^{best} based on $\breve{x}_n$, $\breve{g}_n$ initial local best and global best solution
8: For each iteration *t* until I_T main loop
   For each particle *n*
10: $[t+1] = wv_n[t] + \rho_1 r_1 (\breve{g}_n - x_n[t]) + \rho_2 r_2 (\breve{x}_n - x_n[t])$,
   $x_n[t+1] = x_n[t] + v_n[t+1]$,
12: compute $J_n[t+1]^n$ based on the vector of clusters defined by $x_n[t+1]$

$$J_n[t+1] = \sum_{j=1}^{n}\sum_{i=1}^{c} \left(\mu_{ij}\right)^m \left\|o_j - (x_n[t+1])_i\right\|^2$$

14: If $J_n[t+1] < J_n^{best}$ // particle *n* has improved

$$J_n[t+1] = \sum_{j=1}^{n}\sum_{i=1}^{c} \left(\mu_{ij}\right)^m \left\|o_j - (x_n[t+1])_i\right\|^2$$

16: If $J_n[t+1] < J_T^{best}$
   $J_T^{best} = J_n[t+1]$
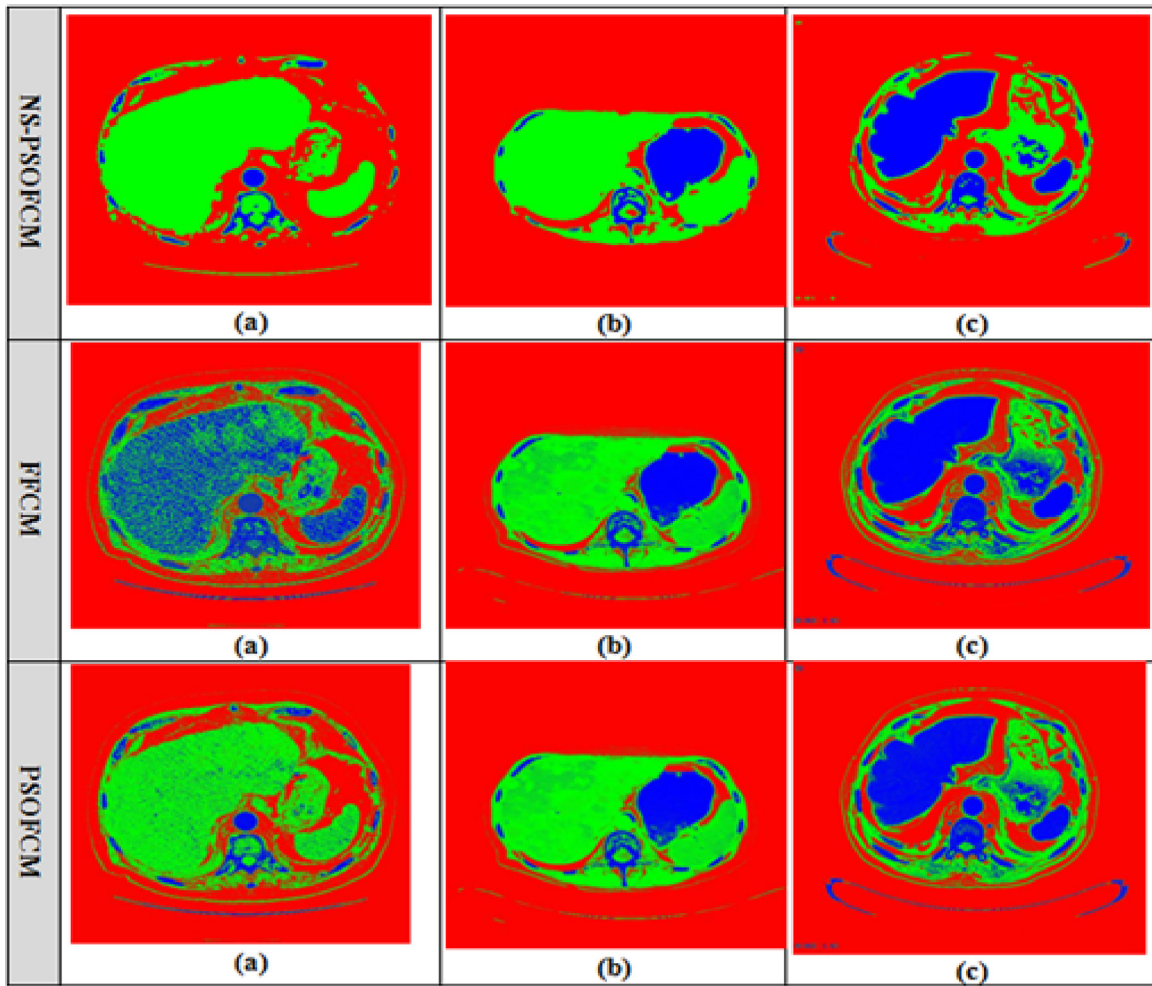 $g_n^{best} = x_n[t+1]$
   end

Fig. 6. The results obtained from the proposed NS-PSOFFCM approach and it's comparison with FFCM and PSOFCM approaches for different slices, NS-PSOFFCM approach in the first row, FFCM algorithm in the second row, and PSOFCM approach in the third row. (a), (b), and (c) are different patient slices.

4.4. Evaluation criteria

4.4.1. Jaccard and Dice Evaluation

The Jaccard Index [34] is very popular and used as a similarity index for binary data as shown in Eq. (15):

$$\text{Jaccard}\,(A_i) = \frac{\left| B_i \cap G_i \right|}{\left| B_i \cup G_i \right|} \tag{15}$$

A_j is the area of overlap, B_j is binary image and G_j is the ground truth image.

The Dice Coefficient [35] is defined as follows:

$$D(A, B) = \frac{2 \left| A \cap B \right|}{\left| A \right| + \left| B \right|} \tag{16}$$

Dice Coefficient measures the extent of spatial overlap between two binary images. It is commonly used to measure the performance of segmentation. Its values range between 0 and 1 which means 0 is no overlap and 1 is perfect agreement.

4.4.2. ANOVA analysis

The significance of the segmentation process on the fitness value was analyzed using statistical analysis one-way analysis of variance (ANOVA) tests. ANOVA analysis was carried out to assess whether the techniques and algorithms used on this paper have statistically

significant differences. For more details about ANOVA readers are referred to [36].

5. Experimental results and discussion

5.1. Description of abdominal CT data set and investigation

The proposed approach will be applied on a complex dataset. The dataset contains more than 105 patients have CT for liver abdominal, each has at least 150 slices with slice resolution of 630×630 pixel and bit depth 24 bits [37]. In abdominal liver CT images, liver is connected to other tissues such as kidney, gastrointestinal tract, stomach, gallbladder, spleen, intercostal muscles, and spinal muscles. Fig. 3 shows the overlap in abdominal CT axial cross section between the intensity of liver and other nearby tissues with strong connections with liver. In automatic liver segmentation phase, fixing scale factor for was a difficult problem. We investigate different CT's and show that, the livers are different from patient to patient in location, shape, size, and number of CT series. The liver is appearing as a largest organ in middle slices.

5.2. Results and discussion

The integrated techniques based on *NS* and FFCM clustering algorithm optimized by PSO to liver CT image segmentation is proposed. Median filter is used to enhance, smooth, and remove noise
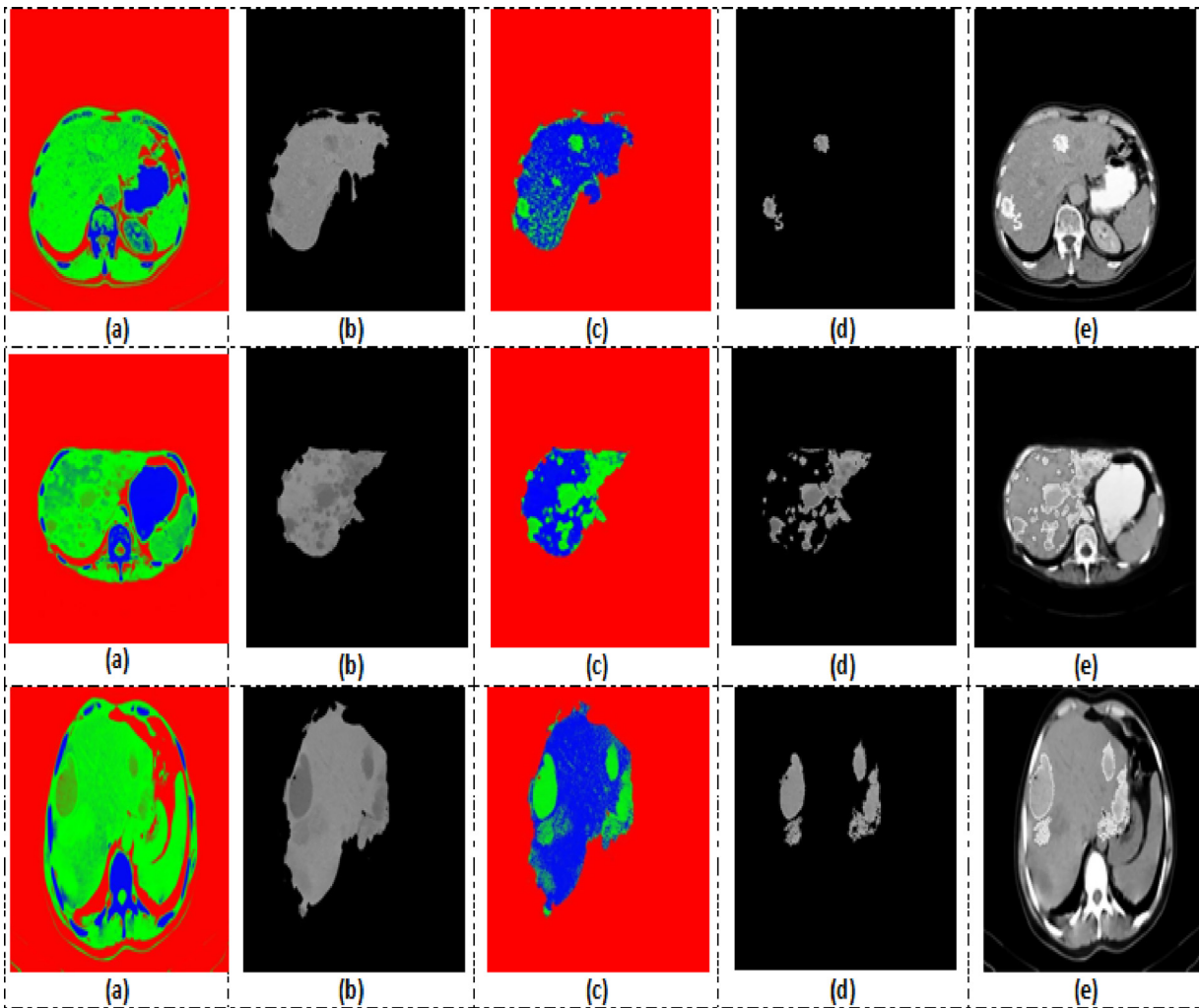
Fig. 7. Results of tumor segmentation using NS-PSOFFCM approach for different patients slices, (a) clustered image using NS-PSOFFCM approach, (b) liver parenchyma segmented and extracted using morphological operators, (c) results of liver tumor clustering using PSOFCM, (d) tumors extracted and segmented from liver parenchyma, (e) Final results of liver tumors in abdominal CT.

with 3×3 window. The image is transformed from image domain to *NS* domain. Each pixel in the *NS* domain represented as *T*, *I*, and *F*. The uniform and non-uniform of the *NS* image is evaluated by the entropy to measure the indeterminacy.

The CT images in *NS* domain are more uniform, homogeneous, and more suitable for segmentation. The FFCM based on bio-inspired PSO is applied to increase the performance, accuracy and reduce time computation. To obtain the FFCM, the histogram of the image is used to increase the computation efficiency. The PSO itself is a very powerful technique and when combined with other computational techniques results in a truly affected approach. PSO particles' velocities are set to zero and their positions are randomly set within the boundaries of the search space. The search space depends on the number of intensity levels. The local neighborhood and global bests are initialized with the worst possible values, taking into account the nature of the problem. Table 2 gives the initial parameters of the PSO for the abdominal CT dataset.

PSO algorithm is referred to fast optimization. However, the computation time for PSO-based segmentation is significantly higher than other methods. Therefore, one needs to be able to choose the parameter values that will result in faster convergence. The cognitive, social, and inertial weights are chosen by taking into account several works focusing on the convergence analysis of the traditional PSO. For instance, to guarantee the convergence

Table 2
Initial parameters of the PSO algorithm and parameters description.

Parameters	PSO	Description
I_T	100	Number of iterations of the PSO algorithm
N	150	Predefined population for multi-segmentation
ρ_1	0.8	Individual weight of particles
ρ_2	0.8	Social weight of particles
W	0.9	Inertial factor
Δv	2	Maximum number of levels a particle can travel between iterations
V_{max}	5	Maximum velocity value for positions
V_{min}	−5	Minimum velocity value for positions

of the process, Jiang et al. [38] presented a set of attraction domains that altogether present a relation between ρ_1, ρ_2, and w, wherein $0 \leq w < 1$ and $\rho_1 + \rho_2 > 0$. Based on the attraction domain in Tarabalka et al. [39], if one chose an inertial coefficient $w = 0.8$, the sum between the cognitive and social components would need to be less than 7, i.e., $\rho_1 + \rho_2 < 7$.

As described in Yasuda et al. [40], a swarm behavior can be divided into intensification (exploitation) and diversification (exploration). The exploitation behavior is related to the convergence of the algorithm. However, if the exploitation level is too high, then the algorithm may be stuck on local solutions. The exploration
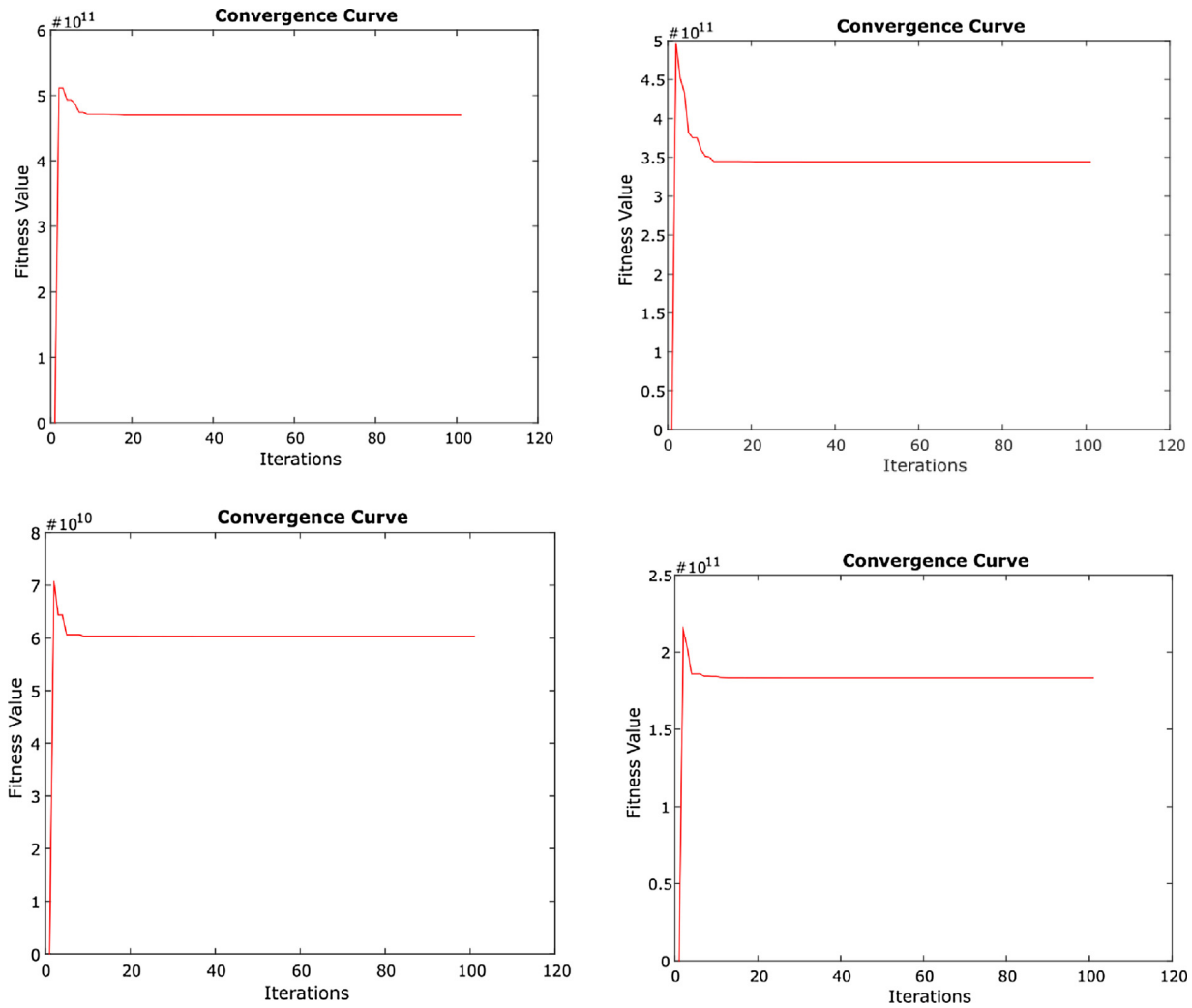
Fig. 8. NS-PSOFFCM convergence for different abdominal CT images.

behavior is related to the diversification of the algorithm which allows exploring new solutions. However, if the exploration level is too high, then the algorithm may take too much time to find the global solution. In NS-PSOFFCM approach, the trade-off between exploitation and exploration can only be handled by adjusting the inertia weight *W*. The exploitation may be improved to converge from optimal solution using a small inertia weight.

The experimental results tested on difficult cases selected from the abdominal dataset. The performance and accuracy are compared with FCM, FFCM, and PSOFCM. In all cases, algorithms are implemented using MATLAB on computer Intel Core I7 2670QM processor (2.2 GHz) and memory 8 GB. The results confirm that the PSO-based segmentation presents efficient results in fitness value, strong ability of the global optimizing, avoids sensitivity to local minima and find optimal solution in short CPU processing time.

The pre-processing stage is very crucial for liver CT to improve the overall visibility of features and enhance a specific sign of malignancy also morphological operators is sensitive to noise, for these reasons pre-processing is very important for liver CT. Fig. 4 shows the results of the effective median filter approach to enhance, remove high frequency, smooth, and remove noise with window size 3 × 3 pixel. The filter run through each element of the image and replace each pixel with the median of its neighboring pixels located in a square neighborhood around the evaluated pixel. Fig. 5 shows the results of the proposed *NS* approach for transforming original CT image to *NS* domain. The results demonstrate that, the

proposed *NS* approach is less sensitive to noise that affect the image segmentation process and removes noise and yields well connected boundaries.

Fig. 6 shows the results of the liver parenchyma clustering using the proposed *NS* based on optimized FFCM approach (NS-PSOFFCM) and the comparison between FFCM and PSOFCM with NS-PSOFFCM. The liver parenchyma is segmented and extracted from clustered abdominal CT image using connected component labeling algorithm (CCL) and opening and closing morphological operators. A morphological processing is an obvious choice to refine the segmentation. The experimental results show that the best predefined shape is diamond with structuring elements being 4. Morphological operations based algorithm works well on the liver whose structure varies between different patients, it focuses less on the structure of the objects as shown in Fig. 7(b). After the segmenting liver from abdominal CT, the post segmentation process is applied to segment tumors. PSOFCM technique is proposed to cluster liver parenchyma as shown in Fig. 7(c). Finally, the tumor is segmented and extracted as shown in Fig. 7(d).

Experimental results show that the traditional FCM and FFCM clustering algorithm are sensitive to noise and stuck in local minima. The results showed that NS-PSOFFCM is generally faster and more robust to local solutions than PSOFCM and FFCM, especially when the dimension of a problem increases. As a result, when the number of dimension increases, a significant difference between the fitness values of the NS-PSOFFCM happens and the NS-

Table 3
Comparison between PSOFCM, FFCM, and NSPSO-FFCM using Jaccard Index and Dice Coefficient.

IM.	NSPSO-FCM		FFCM		PSO-FCM	
	Jaccard	Dice	Jaccard	Dice	Jaccard	Dice
1	0.379	0.5497	0.3338	0.5005	0.3439	0.5118
2	0.3556	0.5246	0.3136	0.4775	0.3205	0.4854
3	0.1692	0.2894	0.1477	0.2574	0.1494	0.2599
4	0.3825	0.5534	0.3095	0.4727	0.3404	0.5079
5	0.2423	0.3901	0.1753	0.2983	0.1898	0.3191
6	0.3789	0.5496	0.3482	0.5166	0.3497	0.5182
7	0.3792	0.5499	0.3484	0.5168	0.3499	0.5184
8	0.3715	0.5418	0.2993	0.4607	0.331	0.4973
9	0.3278	0.4938	0.2588	0.4111	0.2712	0.4267
10	0.2435	0.3916	0.1847	0.3117	0.1982	0.3309
11	0.3705	0.5407	0.3422	0.5099	0.3433	0.5112
12	0.2103	0.3475	0.1888	0.3176	0.1903	0.3197
13	0.2973	0.4584	0.2492	0.3989	0.2628	0.4163
14	0.3234	0.4887	0.258	0.4102	0.2713	0.4268
15	0.3698	0.5399	0.2967	0.4576	0.3252	0.4908
16	0.2151	0.354	0.188	0.3164	0.1902	0.3196
17	0.3368	0.5039	0.3083	0.4713	0.3096	0.4728
18	0.1812	0.3068	0.1618	0.2785	0.1632	0.2807
19	0.1894	0.3185	0.1711	0.2922	0.1726	0.2944
20	0.194	0.325	0.1393	0.2445	0.1452	0.2536
21	0.2802	0.4377	0.2255	0.368	0.2365	0.3826
22	0.3739	0.5443	0.3467	0.5149	0.348	0.5164
23	0.2299	0.3739	0.1576	0.2723	0.1767	0.3004
24	0.2931	0.4533	0.2359	0.3818	0.2471	0.3962
25	0.319	0.4837	0.264	0.4178	0.2814	0.4391
26	0.3666	0.5365	0.3346	0.5014	0.3362	0.5032
27	0.3725	0.5428	0.3428	0.5106	0.3442	0.5122
28	0.3895	0.5606	0.317	0.4814	0.3412	0.5088
29	0.3199	0.4847	0.2691	0.4241	0.2847	0.4432
30	0.3783	0.5489	0.347	0.5152	0.3485	0.5169

PSOFFCM and PSOFCM shows better results than FFCM in higher dimensions. The experiments on abdominal CT images with noise and non-uniform demonstrate that the proposed approach can reduce the indeterminate of the abdominal CT images and perform optimum clusters with better results especially in noisy and non-uniform cases.

The evidence of the convergence speed is provided in Fig. 8 where it is possible to discriminate how the objective function decreases along the iterations, avoid being trapped in local minima and get the best solutions in less iterations. The plots in Fig. 8 are extracted from four images selected from the dataset with different degrees of complexity. From these figures, the NS-PSOFFCM approach is able to find the best solutions in less than 10 iterations, this fact demonstrates the performance of the proposed algorithm. In order to compare the results obtained using PSOFCM, FFCM, and NS-PSOFFCM based on Jaccard Index and Dice Coefficient are shown in Table 3. As can be seen, NS-PSOFFCM approach gives better accuracy than PSOFCM and FFCM approaches. Figs. 9–11 show the best clustering for NS-PSOFFCM, FFCM, and PSOFCM, respectively. While, Fig. 12, shows the comparison between NS-PSOFFCM, FFCM, and PSOFCM approaches based on Dice Coefficient. NS-PSOFFCM approach has higher and more accuracy than FFCM and PSOFCM approaches. Also, the comparison between NS-PSOFFCM, FFCM, and PSOFCM approaches based on Jaccard Index. As can be seen NS-PSOFFCM approach gives better and accurate results than FFCM and PSOFCM approaches as shown in Fig. 13.

The ANOVA analysis is performed on multiple populations for each one of the results obtained from NS-PSOFFCM, FFCM, and PSOFCM approaches as shown in Table 4. As can be seen the NS-PSOFFCM gives best values. The $p-value$ here is less than 0.05. This is means that NS-PSOFFCM, FFCM, and PSOFCM are significantly different.

The box plots and whiskers are used to indicate whether the distribution of the fitness clustering values obtained from the
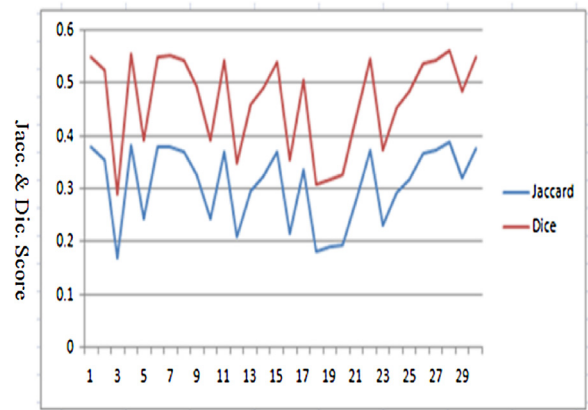

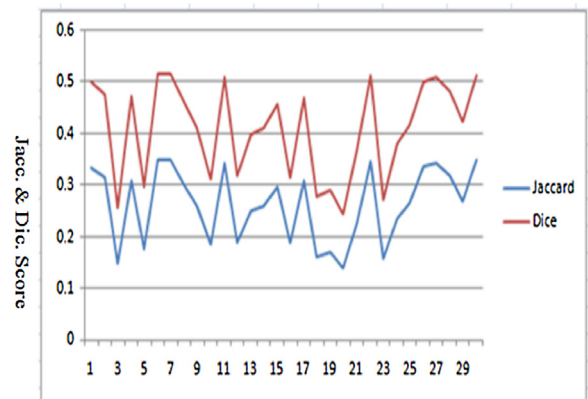**Fig. 9.** NS-PSOFFCM fitness values using Jaccard and Dice similarity measures.

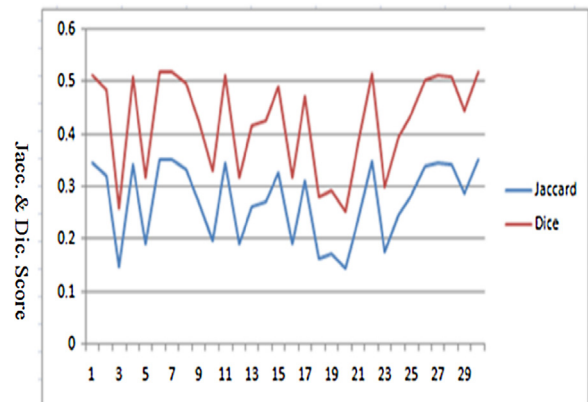**Fig. 10.** FFCM fitness values using Jaccard and Dice similarity measures.

Fig. 11. PSOFCM fitness values using Jaccard and Dice similarity measure.

implemented algorithms. They show the median, the quartiles, and the smallest and greatest values in the distribution [41]. Fig. 14 shows the box plot of Jaccard Index for three approaches applied in this paper. The best results obtained from NS-PSOFFCM, with mean value 0.31. Fig. 15 shows the box plot of Dice Coefficient for the three approaches. The best results obtained also from NS-PSOFFCM with mean value 0.47.

6. Conclusions and future works

In this paper, a new segmentation approach has been proposed for classifying the pixels of liver parenchyma, tumors and other

Table 4
ANOVA analysis for fitness values obtained from NS-PSOFFCM, FFCM, and PSOFCM: (SS) sum of squares, (MS) mean squares, (s) standard deviation, (MSE) mean square error.

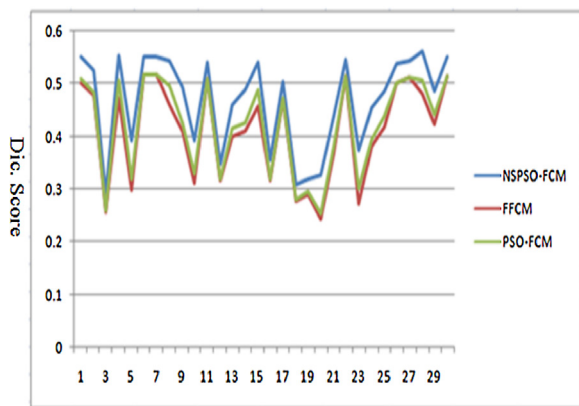| Method	Sim.	ANOVA Analysis						
		SS	MS	F-stat.	p-value	SS err.	MSE	s
NS-PSOFCM	Jac. &Dice	0.375	0.375	56.222	4.2640e−010	0.387	0.007	0.082
FFCM	Jac. &Dice	0.329	0.329	48.216	3.6428e−009	0.396	0.007	0.083
PSOFCM	Jac. &Dic	0.340	0.340	49.309	2.6918e−009	0.400	0.007	0.083

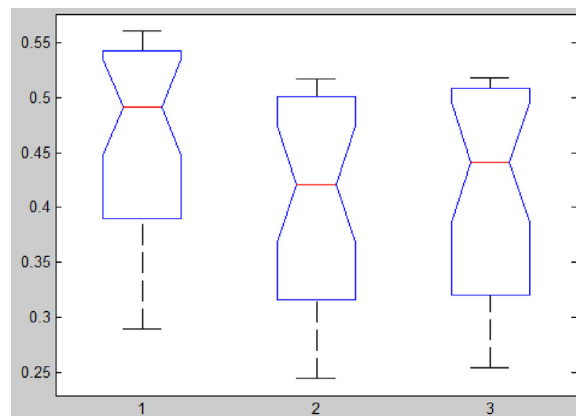**Fig. 12.** Comparison between NS-PSOFFCM, FFCM, and PSOFCM using Dice Coefficient.

Fig. 15. Box plot comparison between (1) NS-PSOFFCM, (2) FFCM, and (3) PSOFCM using Dice Coefficient.
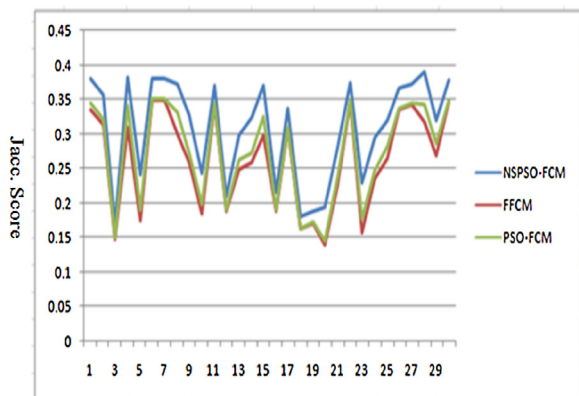

Fig. 13. Comparison between NS-PSOFFCM, FFCM and PSOFCM using Jaccard Index.
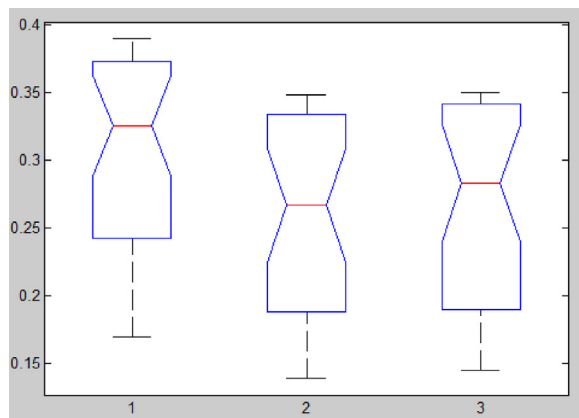

Fig. 14. Box plot comparison between (1) NS-PSOFFCM, (2) FFCM, and (3) PSOFCM using Jaccard Index.

organs in the abdominal CT images into different homogeneous regions. The new approach based on neutrosophic set approach for transforming image domain to *NS* domain to remove noise and enhance CT image. Then, the image is passed to PSOFCM segmentation approach to segment abdominal CT. From all this analysis using difficult dataset for CT liver segmentation using three approaches for image segmentation FFCM, PSOFCM, and NS-PSOFFCM, we can conclude the following points:

1. An effective new *NS*-based pre-processing approach is used to remove noise and enhance CT images in neutrosophic domain.
2. Fuzzy clustering algorithm is able to obtain the approximate boundaries of potential components of interest. However, the standard FCM concerned with the intensity information only. It is not robust enough for all segmentation types, due to noise and artifacts.
3. Computational complexity is largely reduced using the proposed approach.
4. The PSO itself is a very powerful technique and successfully combined with fuzzy sets for abdominal CT image segmentation.
5. PSO being a meta-heuristic with the choice of the parameters having a large effect on it performance makes it hard to evaluate as a general optimization technique.
6. The integrated algorithms tested on difficult abdominal CT dataset and proved to give better results visually as well as objectively.
7. In experimental results, the comparison between NS-PSOFFCM, PSOFCM, and FFCM for CT liver image segmentation. The results indicate that the NS-PSOFFCM is more robust and accurate than other two approaches with fast convergence to optimal solution and less computational time.

In the future research a more theoretical analysis of performance and convergence properties when using a PSO-based image segmentation algorithm may be conducted and the NS-PSOFFCM approach will be evaluated on the real-time deployment.

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