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Segmentation by Fractional Order Darwinian Particle Swarm Optimization Based Multilevel Thresholding and Improved Lossless Prediction Based Compression Algorithm for Medical Images

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ABSTRACT The image segmentation refers to the extraction of region of interest and it plays a vital role in medical image processing. This work proposes multilevel thresholding based on optimization technique for the extraction of region of interest and compression of DICOM images by an improved prediction lossless algorithm for telemedicine applications. The role of compression algorithm is inevitable in data storage and transfer. Compared to the conventional thresholding, multilevel thresholding technique plays an efficient role in image analysis. In this paper, the Particle Swarm Optimization (PSO), Darwinian Particle Swarm Optimization (DPSO), and Fractional Order Darwinian Particle Swarm Optimization (FODPSO) are employed in the estimation of the threshold value. The simulation results reveal that the FODPSO-based multilevel level thresholding generate superior results. The fractional coefficient in FODPSO algorithm makes it effective optimization with fast convergence rate. The classification and blending prediction-based lossless compression algorithm generates efficient results when compared with the JPEG lossy and JPEG lossless approaches. The algorithms are tested for various threshold values and higher value of PSNR indicates the proficiency of the proposed segmentation approach. The performance of the compression algorithms was validated by metrics and was found to be appropriate for data transfer in telemedicine. The algorithms are developed in Matlab2010a and tested on DICOM CT images.

INDEX TERMS Compression, Darwinian Particle Swarm Optimization, Fractional Order Darwinian Particle Swarm Optimization, Particle Swarm Optimization, segmentation, thresholding.

I. INTRODUCTION

Image segmentation refers to the process of extraction of the desired region of interest. In medical images, the region of interest represents anomalies or anatomical organs. Image compression role is inevitable for data storage and transfer in telemedicine. The lossless compression algorithms are preferred for medical images since the reconstructed image quality is good for the validation by physicians. The thresholding is a classical segmentation technique and many variants like iterative thresholding, bi-level thresholding, local thresholding based on specific features and thresholding based on optimization techniques are there in literature.

Moallem *et al.* [1] used Adaptive Particle Swarm Optimization (APSO) for optimal selection of threshold in benchmark images; fewer error rates were produced when compared with Otsu's and Genetic algorithm (GA).

J. Anitha *et al.* made a comparative analysis of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) with Self Organizing Map neural network for the classification of abnormal retinal images; PSO based optimization generates better results than GA [2]. Fahd *et al.* [3] proposed a multilevel thresholding method for the segmentation of images using PSO in which the fitness function was evaluated by using quantitative function method. Chiang Heng Chien used multi-objective particle swarm optimization (MOPSO) in Monte Carlo localization (MCL) algorithm to localize the position of the robot; the simulation results reveal that the localization performance was greatly improved and the convergence quality was maintained [4]. Uma *et al.* [5] applied different optimization techniques like GA, Ant Colony Optimization (ACO) and PSO techniques for the fractal image compression. The ACO based fractal images compression produces satisfactory results than GA and PSO. The PSO finds its role in choosing the optimum wavelet for the image compression; the fitness function was designed in terms of the Mean Square Error (MSE) and the sum of the node entropy. Better results were produced when compared with the global soft thresholding wavelet compression algorithm [6].

Muruganandham A. proposed fast fractal image compression by using PSO; MSE is used as the stopping criterion between range block and domain block and the usage of PSO reduces the encoding time [7]. Adithya Alva proposed a multilevel thresholding segmentation technique based on Tsallis Entropy and Half-life Constant PSO, better PSNR and optimum objective function value when compared with basic optimization algorithms like Genetic Algorithm (GA), Bacterial Foraging (BF) and PSO [8]. Pedram Ghamisi used Darwinian Particle Swarm Optimization (DPSO) for image segmentation in remote sensing applications; the DPSO method has better efficiency in terms of CPU time, selection of optimal threshold value and fitness value [9]. The DPSO find its application in the segmentation of ultrasound images also; the region extraction is done initially, that may be rectangle, circle or random shape and DPSO is applied to obtain more optimized region than the traditional PSO; time and computational complexity is much reduced when compared with the PSO and Genetic algorithm [10]. Vijay *et al.* [11] proposed enhanced DPSO for the segmentation of brain tumor and Adaptive Neurofuzzy inference system for the classification and detection of a tumor in the brain; DPSO gives better accuracy than PSO with less computation time and iteration. Ghamisi *et al.* [12] used Fractional-Order Darwinian Particle Swarm Optimization (FODPSO) for the multispectral and hyperspectral image segmentation; better results are produced when compared with Otsu multilevel thresholding technique and is fast when compared with other classical bio-inspired methods.

Ali *et al.* [13] coupled Fractional-Order Darwinian Particle Swarm Optimization and Mean Shift Clustering algorithm for MRI Brain image segmentation and evaluated by metrics like Jaccard coefficient and accuracy, better results were produced when compared with Fuzzy C Means Clustering (FCM), Mean Shift (MS), PSO, and DPSO techniques. In [14], multithresholding based on various optimization algorithms have been analysed, Brownian heuristic optimization generates efficient results. The firefly with levy flight optimization was found to be efficient for the multithresholding segmentation of gray scale images when compared with the classical firefly optimization [15]. The less parameter tuning in harmony search optimization makes it an efficient one for multithresholding segmentation [16], [17]. A hybrid optimization scheme comprising of whale and moth flame techniques was found to be efficient for the segmentation of gray scale images [18]. The hybrid segmentation algorithm along with the least square predictors was proposed for the lossless compression of medical images; efficient results were produced when compared with the JPEG 2000, CALIC, EDP and JPEG-LS algorithms [19]. The minimum rate predictors based 3D compression algorithm was proposed for the medical images [20]. The prediction based algorithm also gains its importance in lossy data hiding technique [21]. The vector quantization based lossy prediction algorithm generates satisfactory results for medical images [22]. The lossless and lossy prediction compression algorithm based on feed forward neural network with optimization technique was proposed in [23].

This research work proposes PSO and its variants like DPSO and FODPSO for the multilevel thresholding application in abdomen CT medical images for the extraction of ROI. For lossless compression of medical images, classification and blending prediction technique was proposed. The materials and methods describe the data acquisition, variants of PSO algorithm and its parameters tuning. Finally, the algorithms output, performance analysis, and conclusions are drawn.

II. MATERIALS AND METHODS

A. DATA ACQUISITION

The algorithms have been tested on real-time DICOM CT images of the abdomen. The images are obtained from Metro Scans and Research Laboratory, Thiruvananthapuram acquired from Optima CT machine with a slice thickness of 0.6mm. The 7 CT abdomen data sets were used in this research work for segmentation and 6 CT abdomen data sets were used for the analysis of compression algorithms.

B. MULTILEVEL THRESHOLDING

The thresholding is a basic segmentation algorithm and it is a similarity-based approach. The working principle of thresholding technique relies on the threshold value such that the pixels with a gray value higher than the threshold value are labelled as first class, while the pixels with a gray value less than threshold belongs to a second class. The extraction of a region of interest from the image based on the single threshold value is termed as bilevel thresholding.

Consider an image represented by K gray levels, bilevel thresholding can be written as follows

$$R_0 = \{i(x, y) \in I | 0 \leq i(x, y) \leq th - 1\} \quad (1)$$

$$R_1 = \{i(x,y) \in I | th \leq i(x,y) \leq th - 1\} \quad (2)$$

The multilevel thresholding is based on the multiple threshold values and creates an output image with multiple regions as follows

$$R_0 = \{i(x,y) \in I | 0 \leq i(x,y) \leq th_1 - 1\} \quad (3)$$
$$R_1 = \{i(x,y) \in I | th_1 \leq i(x,y) \leq th_2 - 1\} \quad (4)$$
$$R_i = \{i(x,y) \in I | th_i \leq i(x,y) \leq th_{i+1} - 1\} \quad (5)$$
$$R_m = \{i(x,y) \in I | th_m \leq i(x,y) \leq k - 1\} \quad (6)$$

where $th_1, th_2, th_3, \ldots th_i, \ldots th_k$ represents the different thresholds.

The threshold value is determined by using parametric or non-parametric methods. The parametric method is complex and time consuming since it requires the estimation of probability density function to model each class. The non-parametric method utilizes several factors such as between class variance entropy and error rate.

The two classical methods for the estimation of the threshold value in bilevel thresholding are Otsu's and Kapur's technique. In Otsu's algorithm, maximization between the class variance takes place, while Kapur's algorithm maximizes the entropy. The classical threshold estimation techniques can be easily extended to multilevel thresholding, but computational complexity increases in an exponential manner for each new threshold. The classical thresholding techniques are sensitive to noise and need user defined threshold values. Though iterative and automatic thresholding segmentation techniques are there, the results are not satisfactory. The optimization algorithm is employed for the optimal selection of threshold value. The evolutionary optimization techniques are employed in multilevel thresholding that produces an efficient result than classical techniques in terms of precision, robustness, and speed. In this work, PSO algorithm and its variants are employed for the estimation of the threshold for multi thresholding technique.

1) PARTICLE SWARM OPTIMIZATION (PSO)

PSO was developed by James Kennedy in 1995 for optimizing nonlinear function [24]. PSO is a simple and powerful search technique applied to a variety of search and optimization problems. The PSO algorithm is based on the social behaviour of a colony or swarm of insects such as ants, bees, wasps, and termites; a flock of birds or fish. Each particle in PSO is associated with the position and the velocity. The particles are randomly distributed in design space and the best position is estimated based on the objective function. The particles adjust the velocity and the position based on stored best values. For an unconstraint maximization problem, the objective is to maximize f(Y) with $Y^1 \leq Y \leq Y^u$, where Y^1 represents the lower bound and Y^u represents the upper bound.

The velocity of the swarms has also a due consideration in the process. The initial velocity of the entire population is denoted as $U_i = [U_1, U_2, U_3, \ldots U_N,]^T$

The velocity vector is calculated using the formula.

$$U_{n+1}^i = wU_n^i + \sigma_1\gamma_1\left(\widehat{g_n^i} - Y_n^i\right) + \sigma_2\gamma_2\left(\widehat{l_n^i} - Y_n^i\right) + \sigma_3\gamma_3\left(\widehat{m_n^i} - Y_n^i\right) \quad (7)$$

where $i = 1, 2, 3, \ldots g_n^i, l_n^i$ and m_n^i are local best, neighbourhood best and global best values.

The position vector is represented as follows

$$Y_{n+1}^i = Y_n^i + U_{n+1}^i \quad (8)$$

The coefficients $w, \sigma_1, \sigma_2, and \sigma_3$ are represent inertial influence, the global best, the local best and the neighbourhood best. The parameters $\gamma_1, \gamma_2, and \gamma_3$ represent the random vectors and its value is usually assigned a uniform random number between 0 and 1. The inertial influence parameter 'w' is usually set less than 1. The parameters $\sigma_1, \sigma_2, and \sigma_3$ are constant integer values depicting "cognitive" and "social" components. The parameters are tuned based on the application and in many cases neighbourhood best (σ_3) is set to 0. The PSO has successfully proved its efficiency in robotics, electrical systems, and sports engineering.

2) DARWINIAN PARTICLE SWARM OPTIMIZATION (DPSO)

Although the blessing of PSO was enjoyed for optimization problems, it failed in few problems at certain instances [24]. In fact, there was a necessity for another customized version of PSO to address those problems, which opened up the way for Darwinian Particle Swarm Optimization (DPSO) proposed by Tillet *et al.* [25]. In DPSO, 'n' number of swarms of the test solutions, which does behave as PSO has the possibility of existence at a given time. The regulation provided is the collection of swarms are outlined to simulate natural selection [25]. The main advantage of DPSO is that it is capable of working with multiple swarms at a given time. The PSO is of remote use if the search space is found to be discrete. The proposed DPSO algorithm is being inspired by the binary PSO algorithm. The key concept of DPSO is to run multiple simultaneous PSO algorithms, each one depicts a swarm. The DPSO performance is enhanced when compared with PSO in the escape of local optima. The search in an area is simply discarded when the search tends to a local optimum. The fitness of all particles are evaluated, neighborhood best and local best positions are updated.

3) FRACTIONAL ORDER DARWINIAN PARTICLE SWARM OPTIMIZATION (FODPSO)

In the path of the evolution of PSO, the next existence was Fractional Order Darwinian Particle Swarm Optimization (FODPSO) proposed by Couceiro *et al.* in [26], where the fractional calculation was used to control the convergence rate of the proposed algorithm. As an essence, FODPSO was successfully compared with its former forms akin DPSO and PSO [9]. In extension, a multi-level thresholding based on FODPSO was proposed in [12] where the results were proved to be in favour of FODPSO. In literature [13], magnetic resonance brain image segmentation based on FODPSO was proposed and it grabbed an accuracy of 99.45%, whereas DPSO achieved only 97.08%.

The concept of the fractional differential with a fractional coefficient $\sigma \in C$ of a general signal $x(t)$ proposed by Grunwald–Letnikov definition is represented as follows

$$D^{\alpha}[x(t)] = \lim_{h\to 0}\left[\frac{1}{h^{\alpha}}\sum_{k=0}^{-\infty}\frac{(-1)^{k}\Gamma(\alpha+1)x(t-kh)}{\Gamma(k+1)\Gamma(a-k+1)}\right] \tag{9}$$

The discrete time implementation of the above expression is as follows

$$D^{\alpha}[x(t)] = \left[\frac{1}{T^{\alpha}}\sum_{k=0}^{-\infty}\frac{(-1)^{k}\Gamma(\alpha+1)x(t-kT)}{\Gamma(k+1)\Gamma(a-k+1)}\right] \tag{10}$$

The expression of fractional order particle swarm optimization for multilevel thresholding is represented as follows

$$\begin{aligned} D^{\alpha}\left[v_{n+1}^{i}\right] = \sigma_1\gamma_1\left(\widehat{g_n^i} - Y_n^i\right) + \sigma_2\gamma_2\left(\widehat{l_n^i} - Y_n^i\right) \\ + \sigma_3\gamma_3\left(\widehat{m_n^i} - Y_n^i\right) \end{aligned} \tag{11}$$

The computation complexity increases linearly with γ, FODPSO presents a $O(\gamma)$ memory requirement. For $\gamma = 4$ the differential derivative is f18 expressed as follows

$$\begin{aligned} v_{t+1}^{n} &= \alpha v_t^n + \frac{1}{2}\alpha v_{t-1}^{n} + \frac{1}{6}\alpha(1-\alpha)v_{t-2}^{n} \\ &\quad + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)v_{t-3}^{n} + \rho_1\gamma_1\left(\widehat{g_t^n} - x_t^n\right) \\ &\quad + \rho_2\gamma_2\left(\widehat{x_t^n} - x_t^n\right) + \rho_3\gamma_3\left(\widehat{n_t^n} - x_t^n\right) \end{aligned} \tag{12}$$

The parameter α is termed as fractional calculus and DPSO is a special case of FODPSO with $\alpha = 1$.

4) CLASSIFICATION AND BLENDING PREDICTION BASED LOSSLESS COMPRESSION ALGORITHM

The lossless compression algorithm proposed here is based on the idea of blending predictors from Seeman and Tiseher [27]. The classical predictor predicts well in the presence of sharp horizontal edges. The proposed prediction scheme estimates the set of neighbouring pixels into which the blending of the static predictor is performed. The procedure is similar to the initial stage of vector quantization. The different stages in the lossless compression scheme are as follows.

a: CLASSIFICATION

The pixel to be predicted is represented as $'P'$ and $\emptyset_C$ represents the set of neighbouring pixels. The objective of classification is to find M pixels from the casual context $\emptyset_C$ that have minimum distance vector from the pixel being predicted.

The distance to the pixel being predicted is expressed as follows

$$D(i,j) = \|u(i,j) - u(x,y)\| \tag{13}$$

$$D(i,j) = \sum_{K=1}^{D}|u_K(i,j) - u_K(x,y)|^2 \tag{14}$$

The set of M pixels with the minimum distance vector represents the blending context $\emptyset_B$. The Euclidean distance is used as a measure for grouping the pixels into cells similar to the design of vector quantizer.

b: BLENDING

The set of static predictors $f = \{f_1, f_2, \ldots f_n\}$ is blended on the blending context $\emptyset_B$ to generate the final prediction. Each predictor from the set f is coupled with a penalty factor G_K. The penalty factor is based on how the pixels are predicted from the context $\emptyset_B$.

The penalty is represented as the mean square error

$$P_K = \frac{\sum_{S(i,j)\in\emptyset_B}[f_K(i,j) - S(i,j)]^2}{M} \tag{15}$$

c: PREDICTION AND ERROR CORRECTION

For every predictor from the set f, the penalty P_K is its inverse weight. It is used to determine the weighted average of the static prediction for pixels prediction.

$$\widehat{S}(x,y) = \frac{\sum_{f_K\in f}\frac{f_K(x,y)}{P_K}}{\sum_{f_K\in f}\frac{1}{P_K}} \tag{16}$$

Prediction for the current pixel is the weighted sum of the predictions of the static predictors with weights which is inversely proportional to penalty factor. The penalty factor of the predictor determines the efficiency of the blending context. The predictors when predicts well, the final prediction will be good and has the capacity to generate a precise current prediction. The predictors that do not predict well on the current blending contest will be blended out by corresponding large penalty factors.

On the blending context $\emptyset_B$, the average error $\bar{e}$ is determined

$$\bar{e}(\emptyset_B) = \sum_{S(i,j)\in\emptyset_B}\frac{\left[\widehat{S}(i,j) - S(i,j)\right]}{M} \tag{17}$$

Depending upon the error of the blending predictor, the final prediction for the current pixel is determined as follows.

$$S(x,y) = \widehat{S}(x,y) + \bar{e}(\emptyset_B) \tag{18}$$

The classification and blending process adjust itself based on the local property of the pixels. The prediction of the current pixel is based on the casual set of neighboring pixels and classification stage eliminates the higher order redundancy in the local image context.

III. RESULTS AND DISCUSSION

This work presents a comparative analysis of PSO Optimization techniques for multi thresholding segmentation of abdomen CT medical images. The PSO and its variants like DPSO and FODPSO algorithms were incorporated in thresholding technique to find optimal threshold value.

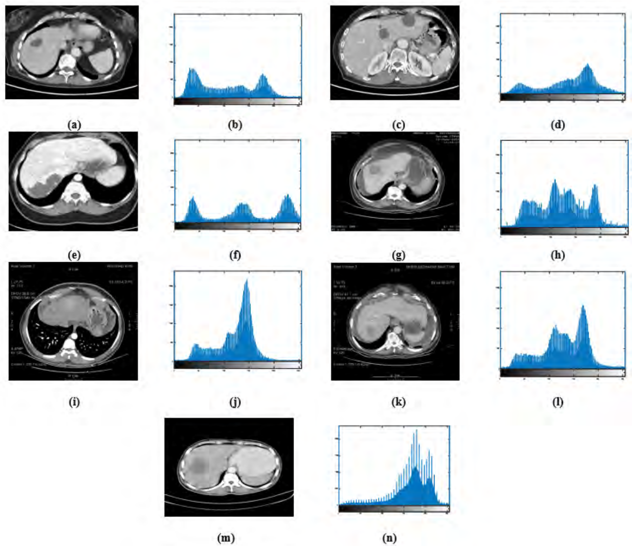

FIGURE 1. (a,c,e,g,i,k,m) Input CT images, (b,d,f,h,j,l) Histogram of input images.

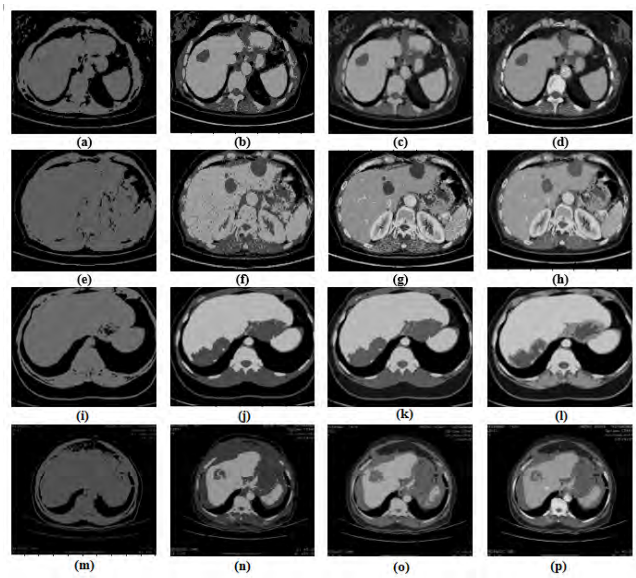

FIGURE 2. FODPSO results for various levels of thresholding (2, 3, 4, 5) corresponding to input CT images (a, c, e, g).

The classification and blending prediction algorithm is a lossless approach that generates efficient compression results for DICOM medical images. The algorithms are developed in Matlab 2013a and processed in Desktop computer with specifications: Intel Core i3 processor, 4 GB RAM, 64-bit operating system. In PSO optimization algorithm, the velocity of particles is set to '0' in the initial stage and their position is randomly set within the boundaries of the search space. Depending on the nature of the problem, the local, neighborhood and global best are initialized with the worst possible values. The population size is vital to generate an overall good solution during optimization within a limited period. The stopping criterion is the fixed number of iteration and it depends on the nature of the problem. The characteristics of DPSO algorithm is to run multiple PSO algorithms simultaneously, each one a different swarm on the same problem under test. Similarly to PSO, the parameters need to be adjusted for producing optimum results are initial warm population count, maximum swarm population count, and stagnancy threshold.

The FODPSO is an extension of DPSO. The fractional coefficient (α) plays a vital role in producing robust results. The DPSO can be termed as a special case of FODPSO with $\alpha = 1$ (without memory). The lower value of α will make the system to get stuck in the local solution (exploitation nature). The larger value of 'α' will present a diversified behavior which allows exploring new solutions. Thus improving the long-term performance (exploration nature). The algorithm will take much time to find the global solution when the exploration level is high. The FODPSO allows the controlling of the convergence rate of particles, thus presenting a more exploiting behavior near the solution vicinities. The optimization algorithms used in this paper are parameterized algorithms and hence the selection of parameters are crucial. The parameter values are chosen in such a manner that faster convergence occurs. The proposed optimization algorithms are tested on abdomen CT images. Figure 1 depicts the input images along with their histograms. Figure 2 depicts the FODPSO output for various threshold values.

TABLE 1. Pathological information of datasets for segmentation.

Dataset ID	Dimension	Pathological information
1	512×512	Benign cyst
2	512×512	Multiple benign cysts
3	512×512	Benign tumor hemangioma
4	512×512	Hepatocellular Carcinoma
5	512×512	Liver cirrhosis, Normal
6	512×512	Malignant lesion with liver cirrhosis
7	512×512	Liver Metastasis

The visual inspection of the resultant images shows that images with a higher level of threshold generate more details. The optimization algorithms are population-based and the results are stochastic, random; hence, each technique was executed 15 times and average values are determined. The average standard fitness values are tabulated in table 1. The ID1 to ID7 depicts the image from 7 data sets. The fitness values are determined for threshold values of 2, 3, 4 and 5. The classical thresholding techniques like entropy thresholding, adaptive thresholding, and local statistics thresholding are sensitive to noise and edge preservation is also poor.

The FODPSO has higher fitness value than the PSO and DPSO. The parameter tuning plays a vital role in the generation of efficient results. The proper parameter selection will give a quick convergence rate. The average standard fitness values are determined for various threshold values. The table 1 depicts the pathological information of datasets for image segmentation. From table 2, it is clear that FODPSO

TABLE 2. Average standard deviation fitness values Of PSO variant segmentation algorithms for test images.

Dataset Details	Threshold Level (th)	PSO	DPSO	FODPSO
ID1	2	4.4202e+003	4.4212e+003	4.4412e+003
	3	4.6945e+003	4.8345e+003	4.9945e+003
	4	5.2092e+003	5.2191e+003	5.2298e+003
	5	5.3072e+003	5.3672e+003	5.3870e+003
ID2	2	5.4164e+003	5.4335e+003	5.4365e+003
	3	6.0090e+003	6.0239e+003	6.0291e+003
	4	6.2042e+003	6.2343e+003	6.2444e+003
	5	6.2054e+003	6.2057e+003	6.4058e+003
ID3	2	7.1646e+003	7.2627e+003	7.2648e+003
	3	8.3378e+003	8.3578e+003	8.4378e+003
	4	8.5190e+003	8.5191e+003	8.6191e+003
	5	8.4957e+003	8.5959e+003	8.6959e+003
ID4	2	4.2616e+003	4.3617e+003	4.4617e+003
	3	4.5997e+003	4.7998e+003	4.9998e+003
	4	5.0865e+003	5.1267e+003	5.1867e+003
	5	5.1756e+003	5.1257e+003	5.2756e+003
ID5	2	4.2954e+003	4.2955e+003	4.4955e+003
	3	4.3960e+003	4.4961e+003	4.9961e+003
	4	5.0506e+003	5.0501e+003	5.1507e+003
	5	5.1054e+003	5.1055e+003	5.2055e+003
ID6	2	4.1009e+003	4.3010e+003	4.9010e+003
	3	5.0228e+003	5.1229e+003	5.3229e+003
	4	5.2065e+003	5.2166e+003	5.5066e+003
	5	5.1882e+003	5.3684e+003	5.5884e+003
ID7	2	7.1386e+003	7.2387e+003	7.5387e+003
	3	7.0692e+003	7.4694e+003	7.8694e+003
	4	7.1950e+003	7.4950e+003	7.9950e+003
	5	8.0514e+03	8.0520e+003	8.0525e+003

has higher fitness values. The fitness values increases as the threshold value increases. Compared to PSO and DPSO, FODPSO has fractional order mechanism that can regulate the convergence rate of swarms there by generating an optimum solution. Moreover, while comparing PSO and Genetic Algorithm (GA), PSO outperforms GA in terms of speed and generation of more local solutions. The PSO is a continuous algorithm, while GA is discrete in nature. The premature convergence is a problem in PSO and it was solved by FODPSO algorithm.

The average thresholds of optimization algorithms are tabulated in table 3. Table 4 represents the PSNR values of multilevel thresholding optimization algorithms. The FODPSO multilevel thresholding technique has high PSNR and low MSE when compared with the other techniques.

The seven abdomen CT data sets are used for the analysis of algorithms. Each dataset comprises nearly 200 images, the result of the typical image from each dataset are depicted here. The algorithms are tested for four different thresholds ($th = 2, 3, 4, 5$). For lower values of threshold say $th = 2$, almost all the images gives poor segmentation result. The under segmentation occurs and for higher values of threshold say $th > 5$, over segmentation occurs. The selection of proper threshold value plays a vital role and can be determined from the value of PSNR. From the table 3, it is evident that PSNR values are within the acceptable range for $th = 4$ and 5.

The FODPSO results in figure 2 depict that, segmentation is better for $th = 4$ and 5. Though for $th = 3$, the result is fair, the objects are not delineated accurately. The higher the value of PSNR, efficient the segmentation quality. The table 3 also clearly indicates that there is not a much considerable difference in the value of PSNR for PSO and DPSO algorithms.

TABLE 3. Average threshold PSO variant segmentation algorithms for test images.

Dataset Details	th	PSO	DPSO	FODPSO
ID1	2	97	98	98
	3	64 148	65 148	65 149
	4	25 84 155	26 84 156	26 85 156
	5	24 80 145 210	25 80 146 211	24 80 145 212
ID2	2	93	94	94
	3	67 156	67 157	68 157
	4	59 139 199	59 139 199	58 138 198
	5	27 89 150 203	28 90 151 204	27 89 150 202
ID3	2	106	106	106
	3	73 180	74 181	74 181
	4	22 89 182	23 90 183	22 89 182
	5	20 77 133 191	21 79 135 193	21 79 135 193
ID4	2	79	79	79
	3	55 149	56 150	55 149
	4	31 94 162	31 94 162	32 95 163
	5	30 90 150 213	31 91 151 214	31 91 150 214
ID5	2	78	78	78
	3	67 190	68 191	67 190
	4	36 106 195	37 107 196	37 107 196
	5	28 83 129 199	29 84 130 200	28 83 129 200
ID6	2	79	80	80
	3	56 149	57 150	57 150
	4	52 133 206	53 134 207	53 134 207
	5	28 87 143 208	28 87 143 208	28 87 142 208
ID7	2	92	93	93
	3	78 186	79 187	79 187
	4	58 145 199	59 146 200	58 145 199
	5	49 129 181 226	50 130 182 227	48 128 181 226

TABLE 4. PSNR values Of PSO variant segmentation algorithms for test images.

Dataset Details	Threshold Level (th)	PSO	DPSO	FODPSO
ID1	2	12.6231	12.6514	13.6514
	3	15.8907	15.9236	16.9246
	4	17.8172	17.9104	18.9114
	5	19.0302	19.1086	20.0313
ID2	2	11.4499	11.5154	12.5174
	3	15.5810	15.6302	16.6312
	4	17.1599	17.1599	18.2123
	5	19.2276	19.2808	20.2282
ID3	2	10.7797	10.1665	11.7797
	3	14.9126	14.9881	15.9891
	4	16.3819	16.5102	17.3819
	5	18.6062	18.7996	19.8996
ID4	2	13.9650	13.9650	14.9750
	3	17.0928	17.1620	18.0928
	4	19.9985	19.9985	20.0799
	5	21.2489	21.3223	22.3391
ID5	2	14.4285	14.4285	15.4395
	3	16.3128	16.4037	17.3128
	4	20.3720	20.4446	21.6546
	5	22.9666	23.0377	24.0178
ID6	2	13.9962	14.0649	15.0649
	3	17.6610	17.7262	18.7282
	4	19.4437	19.5246	20.9266
	5	22.1445	22.1445	23.1049
ID7	2	4.1766	12.6079	13.6559
	3	15.8322	15.8362	16.8374
	4	20.2408	20.2626	21.2408
	5	21.7877	21.7878	22.7223

TABLE 5. Parameters of the PSO algorithm and its variants.

Parameter	PSO	DPSO	FODPSO
Number of Iterations	150	150	150
Population	150	30	25
P1	0.8	0.8	0.8
P1	0.2	0.8	0.8
V_{max}	-5	-1.5	-1.5
V_{min}	+5	1.5	1.5
Minimum Population	-	10	10
Maximum Population	-	50	50
Min swarms	-	2	2
Max swarms	-	6	6
Stagnancy	-	10	10
Fractional coefficient	-	-	0.6

TABLE 6. Pathological information of datasets for compression.

Dataset ID	Dimension	Pathological information
1	512×512	Multiple benign lesions in right lobe & left lobe
2	512×512	Hepatocellular Carcinoma(HCC)
3	512×512	Multiple benign lesions in right lobe & left lobe
4	512×512	Multifocal Hepatocellular Carcinoma, Cholelithiasis
5	512×512	Suggestive Metastasis
6	512×512	HCC with metastatic lymphotomy

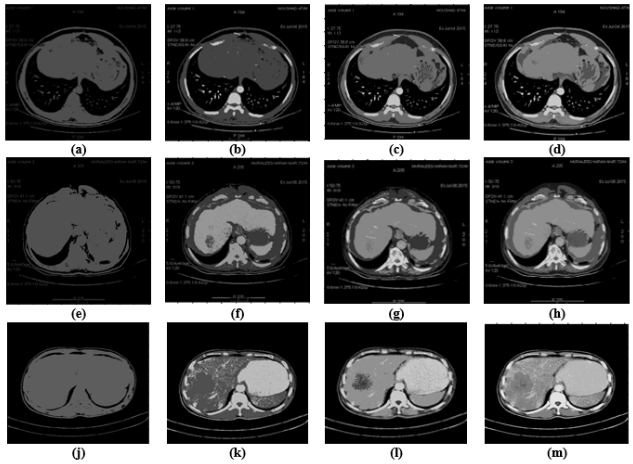

FIGURE 3. FODPSO results for various levels of thresholding (2, 3, 4, 5) corresponding to the input CT images (i, k, m).

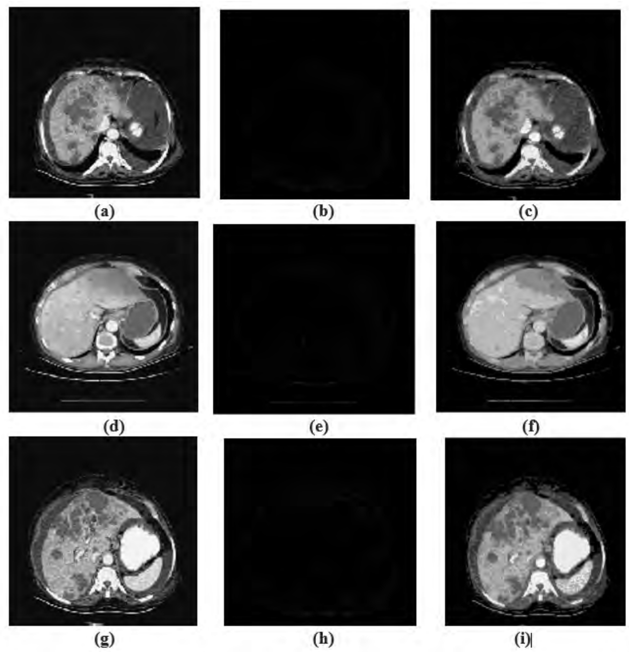

FIGURE 4. The first column represents the input images (ID1, ID2, and ID3), Second column represents the error image, the Third column represents the reconstructed image.

The parameter tuning plays a vital role in the generation of efficient results and the parameters of the algorithms are depicted in table 5. The proper parameter selection will give a quick convergence rate. The average standard fitness values are determined for various threshold values. From table 2, it is clear that FODPSO has higher fitness values. The fitness values increases as the threshold value increases. Compared to PSO and DPSO, FODPSO has fractional order mechanism that can regulate the convergence rate of swarms there by generating an optimum solution. Moreover, while comparing PSO and Genetic Algorithm (GA), PSO outperforms GA in terms of speed and generation of more local solutions. The PSO is a continuous algorithm, while GA is discrete in nature. The premature convergence is a problem in PSO and it was solved by FODPSO algorithm.

The vital features of swarm algorithms are exploitation and exploration. The convergence rate depends upon the exploration and the high level of exploitation will result in local solutions. The exploration is concerned with the diversification of algorithm there by exploring new solutions ensuring reliable performance. The high level of exploration will increase the execution time of the algorithm. The parameters of the PSO algorithm and its variants are depicted in table 4

In DPSO, the balance between these two factors was done by tuning the inertial weight. Higher the value of exploration, better the exploration. The lower value of inertial weight gives much preference for exploitation. In FODPSO, the fractional coefficient (α) ensures global solution by controlling the convergence rate of particles. The computation complexity was greatly minimized in FODPSO since it can run with a small population. The table 6 depicts the pathological information of datasets for image compression.

Let I_{mn} represents the input image and $\widehat{I}_{mn}$ represents the reconstructed image; the validation metrics are expressed as follows.

The PSNR estimates the quality of the compression algorithm. Higher the PSNR value, better the efficiency of the

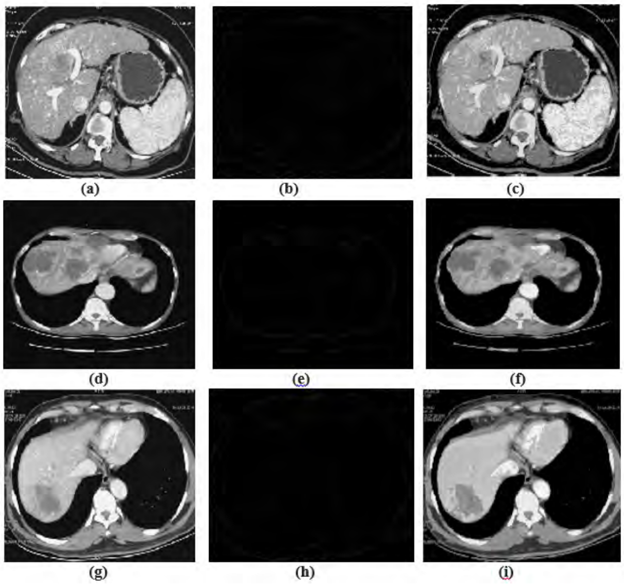

FIGURE 5. The first column represents the input images (ID4, ID5, and ID6), Second column represents the error image, the Third column represents the reconstructed image.

compression algorithm.

$$PSNR = 10 \log \left(\frac{255^2}{MSE} \right) \tag{19}$$

The normalized cross correlation (NCC) is a measure of similarity between the input image and the reconstructed image; higher value of NCC closer to 1 indicates the efficiency of the compression algorithm.

$$NCC = \sum_{i=1}^{m} \sum_{i=1}^{n} \frac{I_{mn} \times \widehat{I}_{mn}}{I_{mn}^2} \tag{20}$$

The higher value of Structural Content (SC) indicates the poor quality of the reconstructed image.

$$SC = \frac{\sum_{i=1}^{m} \sum_{i=1}^{n} (I_{mn})^2}{\sum_{i=1}^{m} \sum_{i=1}^{n} (\widehat{I}_{mn})^2} \tag{21}$$

The LMSE reflects the quality of edges in the reconstructed image when compared with the original image. Higher the value of LMSE, poorer the quality of reconstructed images.

$$LMSE = \frac{\sum_{i=1}^{m} \sum_{i=1}^{n} \left[L\left(I_{mn}\right) - L\left(\widehat{I}_{mn}\right) \right]^2}{\sum_{i=1}^{m} \sum_{i=1}^{n} \left[L\left(\widehat{I}_{mn}\right) \right]^2} \tag{22}$$

The proposed Classification and Blending Prediction (CBP) based Lossless compression algorithm was compared with the JPEG lossy and JPEG lossless algorithms and the performance metrics plots are depicted below in figure 5, 6, 8 and 9. Table 7 depicts the compression ratio

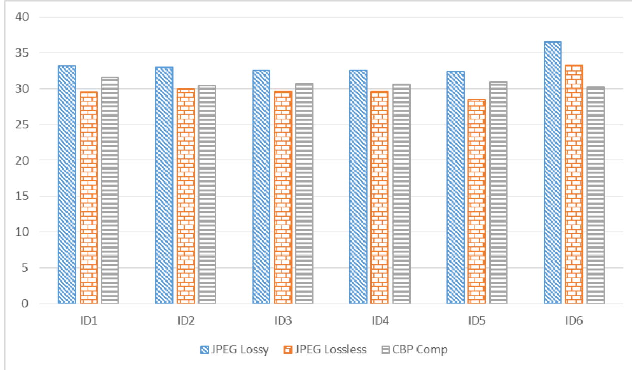

FIGURE 6. PSNR plot of compression algorithms.

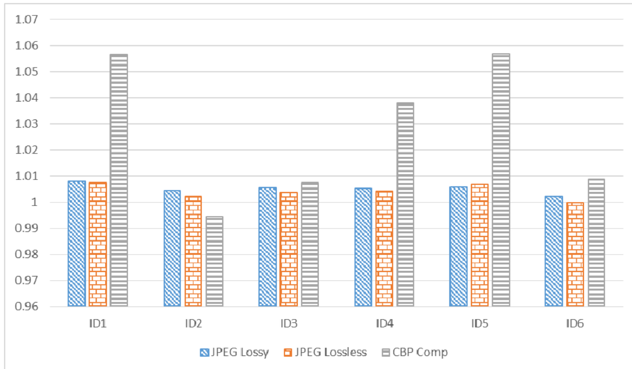

FIGURE 7. The structural content plot of compression algorithms.

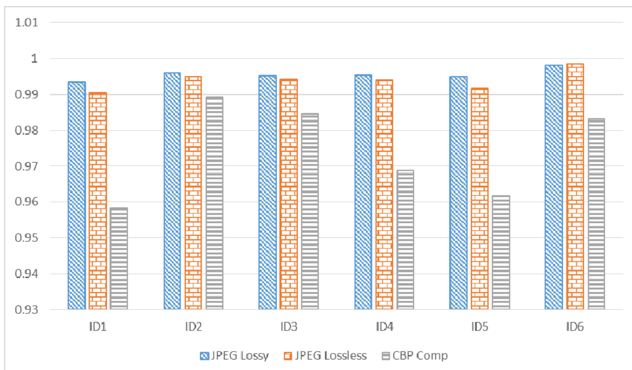

FIGURE 8. Normalized cross correlation plot of compression algorithms.

and execution time of blending prediction based lossless compression algorithm.

The lower the value of NAE, closser to 0 indicates the effeciency of the compression algorithm.

$$NAE = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left| I_{mn} - \widehat{I}_{mn} \right|}{\sum_{i=1}^{m} \sum_{j=1}^{n} (I_{mn})^2} \tag{23}$$

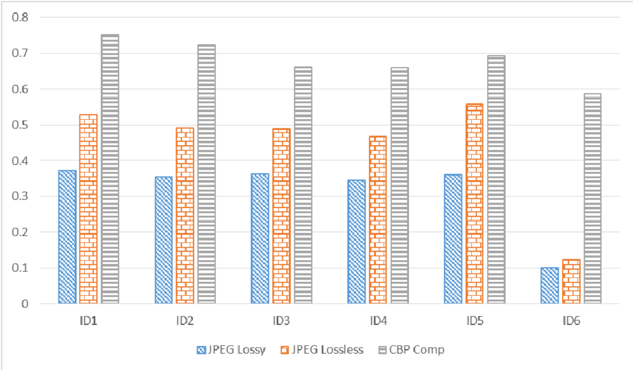

FIGURE 9. LMSE plot of compression algorithms.

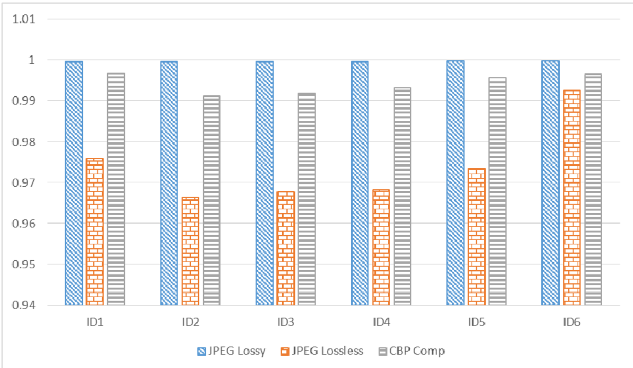

FIGURE 10. FSIM plot of compression algorithms.

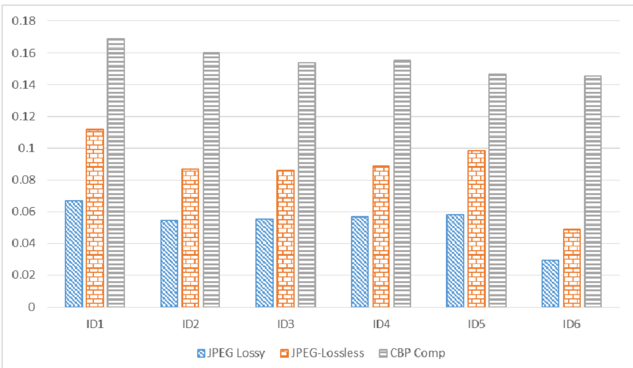

FIGURE 11. NAE plot of compression algorithms.

Higher the value of FSIM, closer to 1 indicates the efficiency of the compression algorithm.

$$FSIM = \frac{\sum_{X\in\Omega} S_L(X).PC_m(X)}{\sum_{X\in\Omega} PC_m(X)} \tag{24}$$

The $S_L(X)$ and $PC_m(X)$ represents the similarity and phase congruency measure.

The performance metrics plots reveal that proposed lossless compression algorithm was found to be efficient when compared with the JPEG lossy and JPEG lossless algorithms. The JPEG lossy algorithm used here comprises of discrete cosine transform and Huffman coder for compression. The JPEG lossless algorithm used here comprises of the Adaptive predictor with Golomb and run length coder.

TABLE 7. Compression ratio add execution time of blending prediction based lossless compression algorithm.

Dataset ID	Uncompressed Size (bytes)	Compressed size (bytes)	CR	Time (s)
1	557056	262144	2.13	8.9162
2	557056	262144	2.13	8.5238
3	557056	262144	2.13	8.9867
4	557056	262144	2.13	8.8085
5	557056	262144	2.13	8.2339
6	557056	262144	2.13	7.6737

IV. CONCLUSION

This research work proposes PSO and its variants like DPSO and FODPSO for the multilevel thresholding of medical images. The classification and blending prediction lossless compression algorithm was proposed in this work for medical images. The PSO based thresholding overcomes the issues of classical Otsu algorithm. The FODPSO is an extension of DPSO with the fractional coefficient controlling the convergence rate of the algorithm. Among the PSO optimization techniques, FODPSO yields efficient results in terms of fitness, PSNR and MSE values. The fractional coefficient favors a higher level of exploration thereby ensuring the global solution of the algorithm. The efficient results are produced when compared with the JPEG lossy and JPEG lossless algorithms and validated by performance metrics. The outcome of this research work will be an aid for telemedicine in the analysis of ROI and compression of images for data transfer. The future work is the hardware implementation of segmentation and compression algorithm by an embedded processor for the development of a portable system for data transfer and analysis.

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