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ORIGINAL ARTICLE

Detecting tumours by segmenting MRI images using transformed differential evolution algorithm with Kapur's thresholding

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Abstract
The speed and accuracy with which the patient affected with brain tumour is diagnosed and monitored, plays a very crucial role in providing treatment to the patient. During the diagnosis of the diseased part, a constant demand is anticipated to easily extract the specific region of interest within the complex medical image. This task of extracting only the diseased portion amid the complex body parts in the complex medical image can be achieved by image segmentation. Accuracy and speed of extracting the points or area of interest within the multipart medical image can be improved by using various evolutionary techniques. Differential evolution (DE) is an efficient evolutionary technique that can be used for solving optimisation problem like image segmentation. The main disadvantage of classical evolutionary technique is its inability to adapt its solution algorithm to a given problem. Owing to this need, more adaptable and flexible algorithms are in demand. Numerous variants of DE exist which differ in their solutions. Here, a variant of differential evolution named as transformed differential evolution (TDE) is presented which has an improved mutation strategy that is optimised to fewer function evaluations. This variant is combined with the Kapur's multi-level thresholding for segmenting magnetic resonance imaging (MRI) images and to extract only the regions of tumour. The results obtained using TDE with Kapur's multi-level thresholding were compared with the results using traditional Kapur's technique and the new results improved profoundly. By introducing TDE in multilevel thresholding, the computational time significantly reduced and the resultant image quality improved greatly.

Keywords Optimal · Variance · PSNR · MSE

1 Introduction

Magnetic resonance imaging (MRI) is an imaging device that makes exhaustive, cross-sectional images within the body. MRI plays a major part in cancer analysis, presentation and cure preparation. With MRI, differentiation between normal and unhealthy tissues is obtained accurately to identify the tumourous cells inside the body. The information given in the MRI images may be complex, and the physicians can take a little longer time to detect the regions of interest. So, to assist them, the technique of image segmentation can be used to detect tumours clearly and accurately.

Segmentation is a technique of grouping any image into multiple regions where pixels in a region have similar attributes. The quality of segmentation is the success of the image analysis system. Segmentation is often needed as a preliminary step for analysing the medical images. Due to the complex nature of medical images, segmenting these images is a challenging and complex task. Thresholding is an effective method for segmenting complex images. Thresholding considers an optimal threshold by which pixels with intensity value higher than the optimal threshold are grouped into one class and the rest into another class. When image is segmented into two diverse type of classes, the technique is called bi-level thresholding. When images are segmented into more than two classes, it is called multi-level thresholding. Image segmentation

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performed on the basis of multi-level thresholding is widely used by researchers and scientist to segment complex coloured images. Multi-level thresholding divides an image into several groups by identifying more than one threshold value. Ease of implementation, lesser storage space, improved processing speed are some of the advantages of using thresholding techniques.

Various algorithms are developed for finding optimal threshold value for performing segmentation of images. Thresholding is classified into parametric and nonparametric method. In parametric method, value of probability density function has to be calculated for each class. The nonparametric method employs various methods for evaluating the quality of clusters formed. In this paper, the nonparametric approach of Kapur's technique is employed. This technique is a popular histogram-based thresholding technique where the optimal threshold is assigned by maximising the between class variance. Kapur et al. [1] developed a popular histogram-based thresholding technique for maximising the entropy value. Problems like thresholding are named as unsupervised learning, and these matters can be resolved by means of evolutionary algorithm. Recent researches have used various evolutionary procedures like genetic algorithm, particle swarm optimisation, differential evolution algorithm, etc., to enhance the outcome of thresholding method. Evolutionary algorithm uses the biological procedures of reproduction, recombination, selection and mutation. Storn and Price [2] introduced the differential evolution algorithm (DE) that traces concepts of evolutionary techniques. DE is a simple, population-based algorithm that helps in resolving optimisation issues effectively. The performance and effectiveness of differential evolution algorithm are determined on the basis of control parameter in use and the trial vectors generation strategy. Several variations of differential evolution are considered by altering these parameters.

In this work, a variant of DE is introduced and is named as transformed differential evolution algorithm (TDE). TDE uses three control parameters in the mutation strategy. This strategy is compared with the other traditional alternates to authorise effectiveness of TDE. This strategy is used in image thresholding for segmenting the MRI images to extract regions of tumour. Based on Kapur's technique, multi-level image thresholding is then implemented together with the TDE method to accomplish image segmentation. The initial part of the work details the classical approaches, the proposed variant that was created and Kapur's entropy-based thresholding. The remaining part explains the execution of the variant in multilevel thresholding and the outcomes that were obtained during the study.

1.1 Related works

Tang et al. [3] devised machine vision-based detection technology. Colour-based segmentation technique using binary-coded genetic algorithm was implemented. The results obtained using this technique showed substantial performance. Vese and Tony [4] gave a new multiphase level set framework for segmenting images. This technique used the Mumford and Shah model. The model was validated using numerical results for image and signal denoising. Tao et al. [5] projected a three-level thresholding technique for segmenting images. This technique uses fuzzy partitioning, entropy theory and probability partition. The experiments performed show significant results for the new technique. Kim et al. [6] devised an information-theoretic approach for image segmentation. This technique does not necessitate the image sections to have a specific type of probability distribution and use of particular statistics. This technique does not require any training. Omran et al. [7] created a technique built on dynamic clustering approach with particle swarm optimisation (DCPSO). This method is used for image segmentation. This technique calculates the number of clusters and then groups the dataset with limited user interface. Clustering technique is performed by k-means approach. It was applied on natural and synthetic images, and the results obtained were effective.

Awad et al. [8] implemented a multi-component image segmentation technique with hybrid genetic algorithm and Kohonen's self-organising map. Tests were conducted on various satellite images and the efficacy and strength of the technique was verified. Das et al. [9] describes the usage of differential evolution for automatic clustering of unlabelled dataset. This technique was tested on real-time dataset and a comparative analysis was performed. Maitra et al. [10] created a variant of PSO which was further enhanced by cloning fitter particles. This technique was compared with some of the existing techniques of evolutionary algorithm on clustering data. It uses cooperative and comprehensive learning methods. This method was used for multi-level thresholding for histogram-based image segmentation. This method used both cooperative and comprehensive learning methods. Jin et al. [11] devised a fully automated respiratory phase segmentation technique using single channel breath sound recording of numerous types. Maulik [12] gave an in-depth review on the applications of Genetic algorithm on medical image segmentation.

Ribeiro et al. [13] gave the application of genetic algorithm for regulating the segmentation process of digital images. Gulati and Panwar [14] implemented the genetic algorithm with active contours for image segmentation. Bhandari et al. [15] developed cuckoo search algorithm

(CS) and wind driven optimisation (WDO) for multilevel thresholding using Kapur's entropy. The output obtained shows that the technique developed was accurate and efficient. Manikandan et al. [16] proposed real coded algorithm with simulated binary crossover-based multilevel thresholding. This technique was used for segmenting MRI brain images. Results were compared with the existing techniques like DE, PSO, etc., and the efficiency of the proposed technique was verified. Mesejo et al. [17] developed a hybrid level set approach for medical image segmentation. This approach displayed better performance in comparison with other techniques. Ramadas et al. [18] proposed a variant of differential evolution algorithm named as forced strategy differential evolution (FSDE). This variant was applied to data clustering, and the efficiency of the technique was justified. Arora and Dhir [19] developed a hybrid classification technique built on correlation-based feature selection and classification through regression approach. It classifies the segmented chromosomes into five categories, namely overlapping, bent, touching, straight or noise.

Bermejo et al. [20] implemented Coral Reef Optimisation Algorithm with Substrate Layers (CRO-SL) to the real-coding IR problem variant. The new technique was benchmarked with existing evolutionary and non-evolutionary IR methods. Naidu et al. [21] implemented a naturally inspired firefly algorithm-based multilevel image thresholding for image segmentation by maximising Fuzzy entropy. It is verified that the proposed method displays better performance and CPU time than traditional methods. Scelsi et al. [22] implemented artificial bee colony (ABC) algorithm to find optimal solution for image contrast enhancement. Das et al. [23] devised a quantum-based variant of classical modified genetic algorithm-based FCM for colour MRI image segmentation. The proposed technique was verified to be superior to traditional techniques. Rundo et al. [24] proposed a novel image enhancement method based on genetic algorithm and verified the results to be superior.

2 Methodology

2.1 Classical differential evolution

Differential evolution algorithm takes the input elements in the form of vectors of real numbers. The designated number of vectors is identified casually in an n-dimensional search space. In every iteration, two or more vectors are chosen arbitrarily from the population and are united to form a new vector. Resultant vector is compared with predecided target vector to create trial vector. If trial vector provides a fitter objective function, then the trial vector is accepted into next generation. Mutation, recombination and selection are pursued till some stopping criteria are attained. DE utilises NP candidate solutions of the population indicated by $X_{i,G}$, in which index $i = 1, 2\ldots NP$ constitute population while G represents the generation of population.

Mutation This type of operation makes DE unique in comparison with other evolutionary technique. The weighted difference of vectors in the generation is calculated. For any given variable $X_{i,G}$, arbitrarily choose three vectors $X_{r1,G}$, $X_{r2,G}$ and $X_{r3,G}$ where r_1, r_2, r_3 are diverse from each other. Subsequently donor vector $V_{i,G}$ is calculated as:

$$V_{i,G} = X_{r1,G} + F \times (X_{r2,G} - X_{r3,G}) \tag{1}$$

The mutation factor F is a constant within (0, 2). The above strategy is denoted as DE/rand/1. The mutation function distinguishes one DE strategy from the other.

Crossover/recombination This operation uses prosperous solutions in the population. For each target vector $X_{i,G}$, a trial vector $U_{i,G}$ is generated by using binomial crossover. Using probability $c_r \in [0, 1]$, the elements of donor vector pass in as trial vector. Crossover probability c_r is designated alongside population size *NP*.

$$U_{i,G} = \begin{cases} V_{i,G} & if\ rand_{i,j}[0,1] \le c_r\ or\ if\ j = I_{rand} \\ X_{i,G} & if\ rand_{i,j}[0,1] > c_r\ or\ if\ j \ne I_{rand} \end{cases} \tag{2}$$

where $rand_{i,j} \approx \cup[0, 1]$ is an arbitrary index and I_{rand} is an arbitrary numeral from 1,2, …*N*.

Selection Target vector $X_{i,G}$ is coupled with trial vector $V_{i,G}$ and lowest result from function is taken into succeeding generation.

$$X_{i,G+1} = \begin{cases} U_{i,G} & iff\left(U_{i,G}\right) \le f\left(X_{i,G}\right)\ where\ i = 1, 2, \ldots N \\ X_{i,G} & otherwise \end{cases} \tag{3}$$

2.2 Transformed differential evolution

In TDE, we have used three control parameters. The parameter F1 takes a varying value which lies between (0, 1), and F2 takes the complement of F1. The parameter F3 takes the product of F1 and F2. As three diverse control parameters are considered, the donor vector value is enhanced significantly and hence the effectiveness of TDE algorithm is improved profoundly. As best solution vector is used, this approach settles quicker in comparison with the old approaches having random vectors only. The variables $X_{r1,G}$, $X_{r2,G}$, $X_{r3,G}$ are selected at random. The anticipated approach is stated as:

$$X' = X_{r1,G} + F3 \cdot \left(F1 \cdot \left(X_{\mathrm{best},G} - X_{r2,G}\right) - F2 \cdot \left(X_{\mathrm{best},G} - X_{r3,G}\right)\right) \tag{4}$$

2.3 Kapur's multi-level image thresholding

Kapur's entropy technique is an indeterminate probability entropy technique for multilevel thresholding which was introduced in 1985. Consider an image I with n pixels which has to be segmented into k classes. Let the n optimal threshold values $(t_0, t_1, t_2 \ldots t_k)$ be denoted as Th. The optimal threshold values are gained by maximising the objective function. Kapur's entropy is denoted as:

$$f(Th) = \sum_{i=0}^{k} H_i \tag{5}$$

where H_i is the entropy of ith class. The entropies for each class are denoted as:

$$H_0 = -\sum_{i=0}^{t_0-1} \frac{p_i}{w_0} \ln \frac{p_i}{w_o},$$
$$H_1 = -\sum_{i=0}^{t_1-1} \frac{p_i}{w_1} \ln \frac{p_i}{w_1}, \ldots H_k = -\sum_{i=t_k-1}^{L-1} \frac{p_i}{w_k} \ln \frac{p_i}{w_k} \tag{6}$$

where

$$w_0 = \sum_{i=0}^{t_0-1} p_i, \quad w_1 = \sum_{i=0}^{t_1-1} p_i, \ldots w_0 = \sum_{i=t_k-1}^{L-1} p_i \tag{7}$$

p_i is the probability distribution of the intensity level. $w_0, w_1, \ldots w_k$ is the probability occurrence of the intensity levels.

2.4 Multi-level thresholding using TDE strategy

In this work, we have introduced the variant of differential evolution approach to Kapur's thresholding. This method uses the TDE mutation approach as specified in Eq. 4. The fitness function for the TDE algorithm is calculated using Eq. 5. The flowchart for the anticipated work is illustrated in Fig. 1.

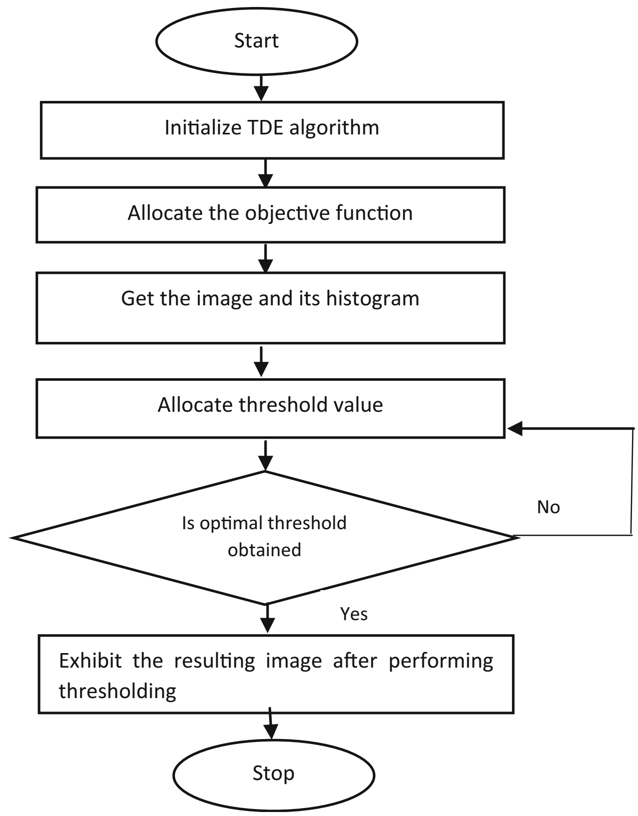


Fig. 1 Flowchart for multi-level thresholding with TDE

3 Results and discussions

3.1 Experimental results of TDE algorithm

TDE is executed using MATLAB R2008b, and the relative outcome attained was tabulated along with the results from traditional mutation strategies. Here, we have taken five traditional mutation strategy (DE/rand/1, DE/rand/2, DE/best/1, DE/best/2, DE/rand-to-best/1) and the proposed technique TDE. The values obtained were compared. The traditional mutation strategies were replaced with the proposed mutation strategy, and TDE was composed. In the experiment conducted, mutation constant F is given the value 0.6 and the crossover probability C_r is given the value 0.8. Fifteen diverse functions were considered, and the results were calculated by setting the value to reach and number of iterations. We have also tested the strategy by setting the dimension as 25 and 50. Few of the outcomes acquired are given in Table 1.

Among each of the above methods, a relative study was done. By fitting size as 25 and 50 and value to reach (VTR) as e−015, the best value, number of function evaluation (NFE) and the CPU time of diverse function approaches are evaluated. Some of the functions achieved good output for all cases of classical DE and TDE algorithm. The outcomes attained reveal that the TDE technique performs with an improved efficiency when compared to the classical DE approach.

Friedman statistical test runs are conducted on TDE algorithms to validate the results. Based on the values from Table 1, the statistical outcomes are tabulated in Table 2. Ranks obtained after the Friedman test are tabulated in Table 3.

Table 1 Comparative results for different strategies of DE with TDE for vtr = 1.e−015

Function	*D*	DE					TDE	Significance
		DE/best/1	DE/rand/1	DE/best-to-rand/1	DE/best/2	DE/rand/2		
Sphere	50	9.724e−016	**6.912e−016**	7.541e−016	9.663e−016	7.173e+0	8.623e−016	−
	25	9.314e−015	9.325e−015	9.537e−015	9.421e−015	6.921e+000	**8.75e−015**	+
Beale	50	3.286e−016	**2.323e−016**	3.712e−016	7.64e−016	7.731e−016	3.123e−016	−
	25	4.216e−015	7.721e−015	**1.128e−015**	1.362e−017	7.54e−015	2.321e−015	−
Booth	50	3.52e−016	2.05e−016	6.078e−016	7.072e−016	8.34e−016	**7.272e−015**	+
	25	1.80e−015	7.552e−016	**1.951e−015**	2.751e−015	6.476e−015	2.124e−015	−
Schwefel	50	**− 1.812e+003**	**2.253e+003**	**− 7.843e+001**	**− 1.383e+003**	**− 1.671e+003**	**− 1.57e+002**	NA
	25	**− 4.212+002**	**− 4.84e+002**	**− 1.672e+003**	**− 4.472e+003**	**− 1.58e+003**	**− 2.321e+003**	NA
Michlewicz	50	**− 7.624e+00**	**− 7.213e+00**	**− 7.48e+00**	**− 6.961e+00**	**− 6.854e+00**	**− 1.37e+002**	NA
	25	**− 7.619e+00**	**− 7.641e+00**	**− 6.871e+00**	**− 7.352e+00**	**− 6.981e+00**	**− 5.455e+00**	NA
Schaffer N.2	50	6.63e−016	8.882e−016	4.434e−016	6.551e−016	8.875e−016	**2.223e−016**	
	25	1.313e−015	1.331e−015	6.664e−016	5.34e−015	1.334e−015	**1.125e-015**	+
Schaffer N.4	50	3.052e−015	2.98e−001	2.923−001	2.934e−001	2.891e−001	**2.794e−001**	+
	25	**2.912e−001**	**2.921e−001**	**2.921e−001**	**2.921e−001**	**2.924e−001**	**2.923e−001**	NA
HimmelBlau	50	1.63e−016	8.053e−016	3.835e−016	9.123e−016	**1.461e−016**	5.456e−016	−
	25	4.813e−015	4.423e−015	**1.906e−015**	3.951e−015	5.145e−015	2.437e−015	+
Bird	50	**− 1.032e+002**	**− 1.063e+002**	**− 1.053e+002**	**− 1.064e+002**	**− 1.033e+002**	**− 1.067e+002**	NA
	25	**− 9.30e+001**	**− 1.045e+002**	**− 1.068e+002**	**− 1.032e+002**	**− 1.046e+002**	**− 6.123e+002**	NA
Extended cube	50	3.33e−015	4.982e−006	6.14e−008	1.931e−005	2.681e+00	**3.298e−015**	+
	25	5.70e−008	5.24e−005	7.10e−008	1.732e−005	2.923e+009	**1.123e−008**	+
Ackeley	50	7.192e−015	6.461e−012	7.992e−015	3.633e−013	3.091e+00	**4.211e−015**	+
	25	7.991e−015	5.022e−015	7.993e−015	3.593e−015	3.218e+00	**3.121e−017**	+
Gold	50	**3.00e+00**	**3.00e+00**	**3.00e+00**	**3.00e+00**	**3.00e+00**	**3.0e+00**	NA
	25	**3.00e+00**	**3.00e+00**	**3.00e+00**	**3.00e+00**	**3.00e+00**	**3.00e+00**	NA
Griewank	50	9.985e−016	9.991e−016	1.68e−013	6.561e−013	1.076e+00	**8.889e−016**	+
	25	**1.473e−002**	9.23e−015	7.882e−015	5.072e−009	1.067e+00	1.897e−005	−
Rastrigin	50	**1.791e+001**	**1.231e+002**	**7.472e+001**	**1.284e+002**	**1.523e+002**	**0**	NA
	25	**3.612e+001**	**1.182e+002**	**8.171e+001**	**1.77e+002**	**1.678e+002**	**1.567e+002**	NA
Rosenbrock	50	9.63e−016	1.071e−008	7.884e−016	3.93e−009	1.071e+005	**2.25e+002**	+
	25	3.982e+00	**1.40e−008**	6.91e−015	1.561e−011	7.156e+004	5.213e−015	−

Bold indicates the best values obtained for each benchmarked function

Table 2 Test statistics

Dimension	50
Chi sq	26.27
Degree of freedom	5
Asymptotic significance	0.00007

Table 3 Mean ranking of various techniques

Strategy	Mean rank on best value	Mean rank on CPU
DE/best/1	2.9	4.6
DE/rand/1	3.1	3.3
DE/best-to-rand/1	2.8	3.4
DE/best/2	4.4	3.5
DE/rand/2	5.1	3.8
TDE	2.4	2.1

The above tabulation validates the fact that the mean rank obtained by TDE for best value and CPU time are the best in assessment to the traditional mutation techniques of DE Algorithm.

3.2 Outcome on image segmentation

TDE approach was executed in MATLAB R2017a and subsequently was merged with the Kapur's technique to perform multi-level image thresholding. This technique was tested on three groups of MRI colour images. The values for optimal threshold for each class of image were calculated and are tabularized in Table 4. Outcomes attained establish that the proposed TDE strategy gives enhanced output for multi-level thresholding in assessment with traditional DE method.

The results tabulated in Table 5 demonstrate improved efficiency for the TDE technique with Kapur's thresholding. The multi-level Kapur's thresholding was then performed few of MRI sample images that were taken from www.sciencephoto.com. The original MRI images along with its histogram and segmented images based on Kapur's and TDE with Kapur's are given in Figs. 2, 3, 4.

The performance of the algorithms used is verified using the peak-to-signal ratio (PSNR) and CPU time. PSNR is the measure of quality between the original image and the segmented image based on mean square error (MSE). It is defined as:

$$\mathrm{PSNR}(\sigma, s) = 20\log_{10}\left[\frac{255}{\sqrt{\mathrm{MSE}(\sigma, s)}}\right] \quad (8)$$

Table 4 Comparison of optimal threshold value

Image	Number of thresholds (m)	Optimal threshold values	
		Kapur's method	TDE with Kapur's
Image 1	1	127	128
	2	52,153	52,154
	3	47,104,184	47,100,189
	4	39,100,175,200	40,102,180,210
Image 2	1	127	130
	2	96,179	98,182
	3	67,135,195	70,142,200
	4	35,89,146,207	40,93,153,215
Image 3	1	125	135
	2	64,188	70,196
	3	85,154,204	85,156,208
	4	56,109,147,214	57,109,150,221

Table 5 Comparison of PSNR value and CPU time

Image	Number of thresholds (m)	PSNR		CPU time	
		Kapur's method	TDE with Kapur's	Kapur's method	TDE with Kapur's
Image 1	2	15.67	15.89	2.4	2.1
	3	16.03	16.12	4.7	4.2
	4	17.12	17.23	6.2	5.8
Image 2	2	13.78	13.98	2.4	2.1
	3	14.34	14.87	4.5	4.1
	4	15.12	15.34	6.86	6.34
Image 3	2	13.54	13.76	2.36	2.13
	3	14.23	14.56	4.3	4.21
	4	15.21	15.34	6.86	5.4

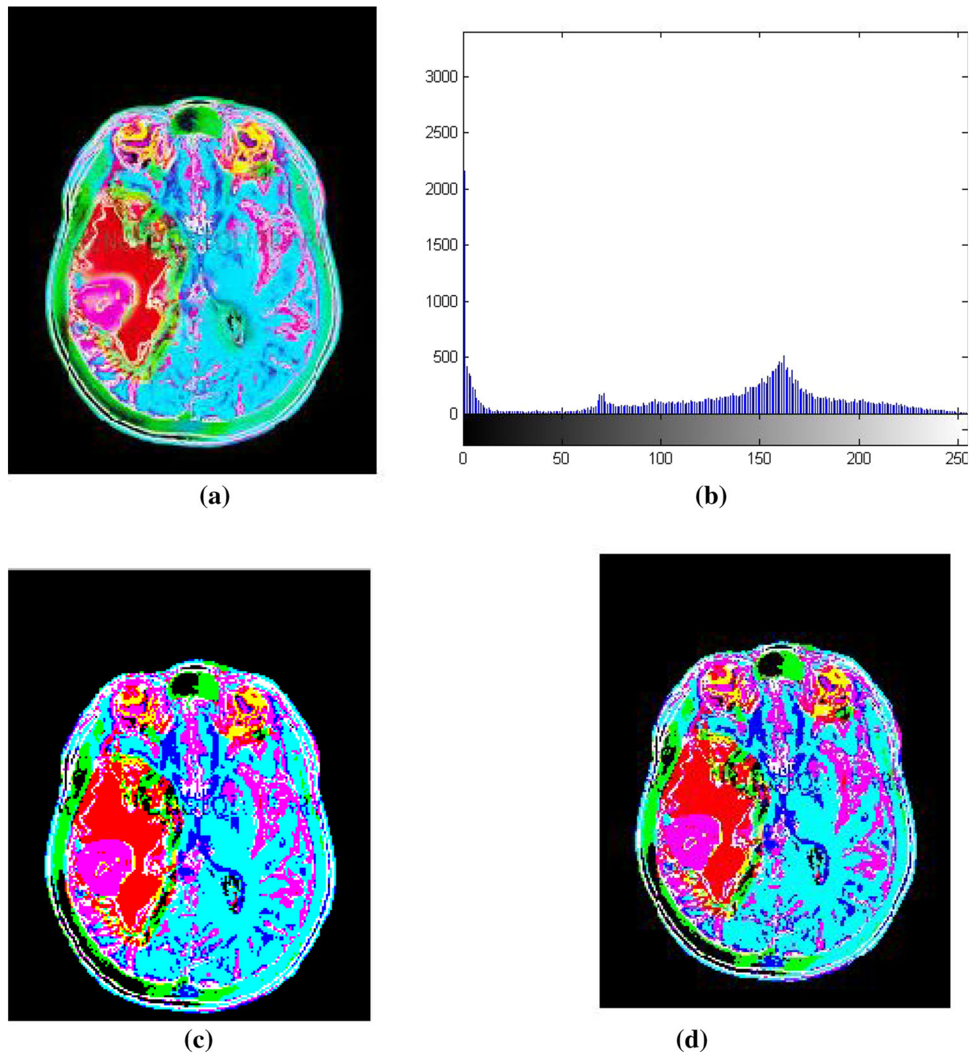


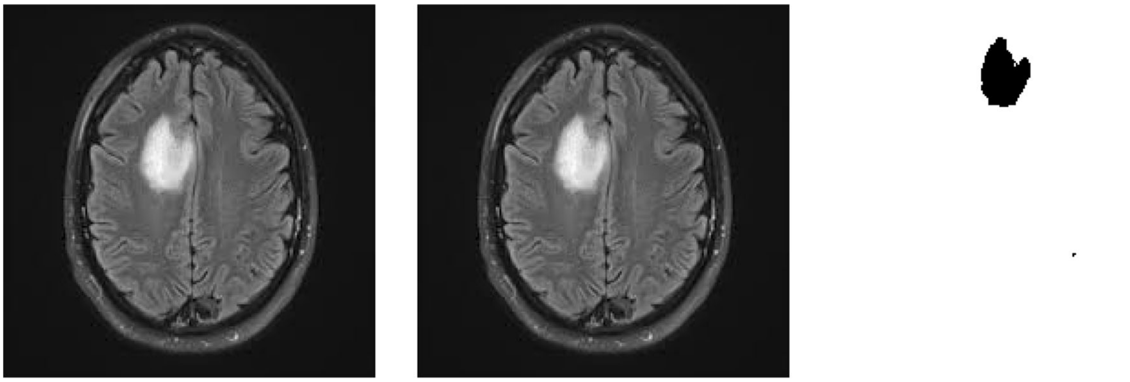
Fig. 2 Segmentation of image 1. **a** Original image, **b** histogram, **c** segmented image using Kapur's, **d** segmented image using TDE with Kapur's

where σ is the original image and s is the segmented image. If the size of image is $m \times n$, then the mean square error (MSE) is defined as:

$$\mathrm{MSE} = \frac{1}{m * n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [\sigma(m,n) - s(m,n)] \tag{9}$$

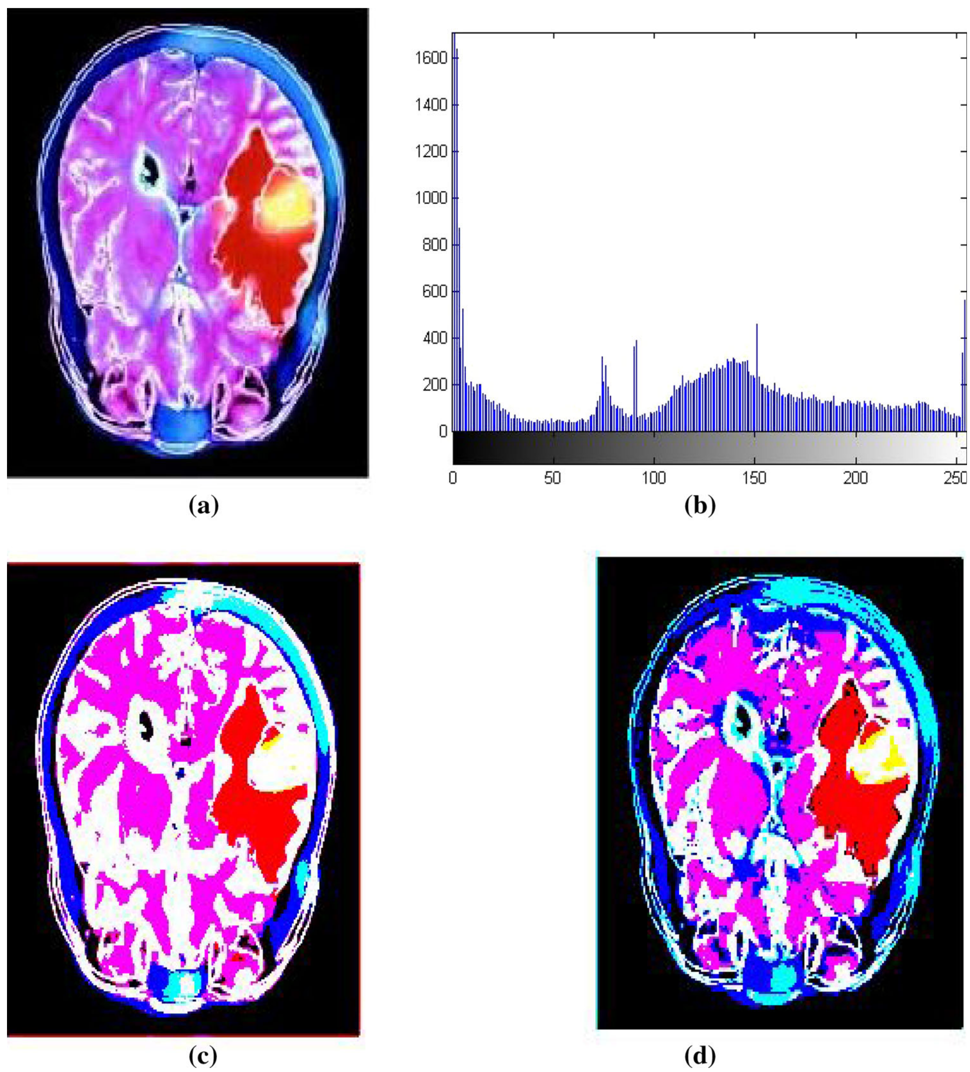
Generally, for any MRI scan, the coloured MRI images are introduced to get a detailed view of the tissues and cells within the specific area of the body part that is to be analysed. These images are quite complex in nature and have some sense of difficulty in differentiating between the healthy tissues and cells against the diseased once. The differentiation is tough especially in cases where the physician tries to interpret the severity of infection. However, by the way of segmenting these complex MRI image, we can extract only those part on the image that has the infection or tumours. This serves larger purpose for the physician while analysing the patients MRI image reports, improving the accuracy in judgement and reducing the time spent on image analysis. The specific segmented portion of tumours for the sample images is shown in Fig. 5.

From the above figure, it is clearly seen that the regions of tumour from image 1 and 2 are segmented and are shown separated in a different colour. Image 3 has no tumour, and its tumour region is shown as blank in Fig. 5f. Using TDE with Kapur's technique, the tumour can be extracted easily from a complex MRI coloured image. The same technique can be applied to ordinary MRI scan images too.



(a) Original image **(b)** Image after thresholding **(c)** Segmented tumour region

Fig. 3 Segmentation of image 2. **a** Original image, **b** histogram, **c** segmented image using Kapur's, **d** segmented image using TDE with Kapur's



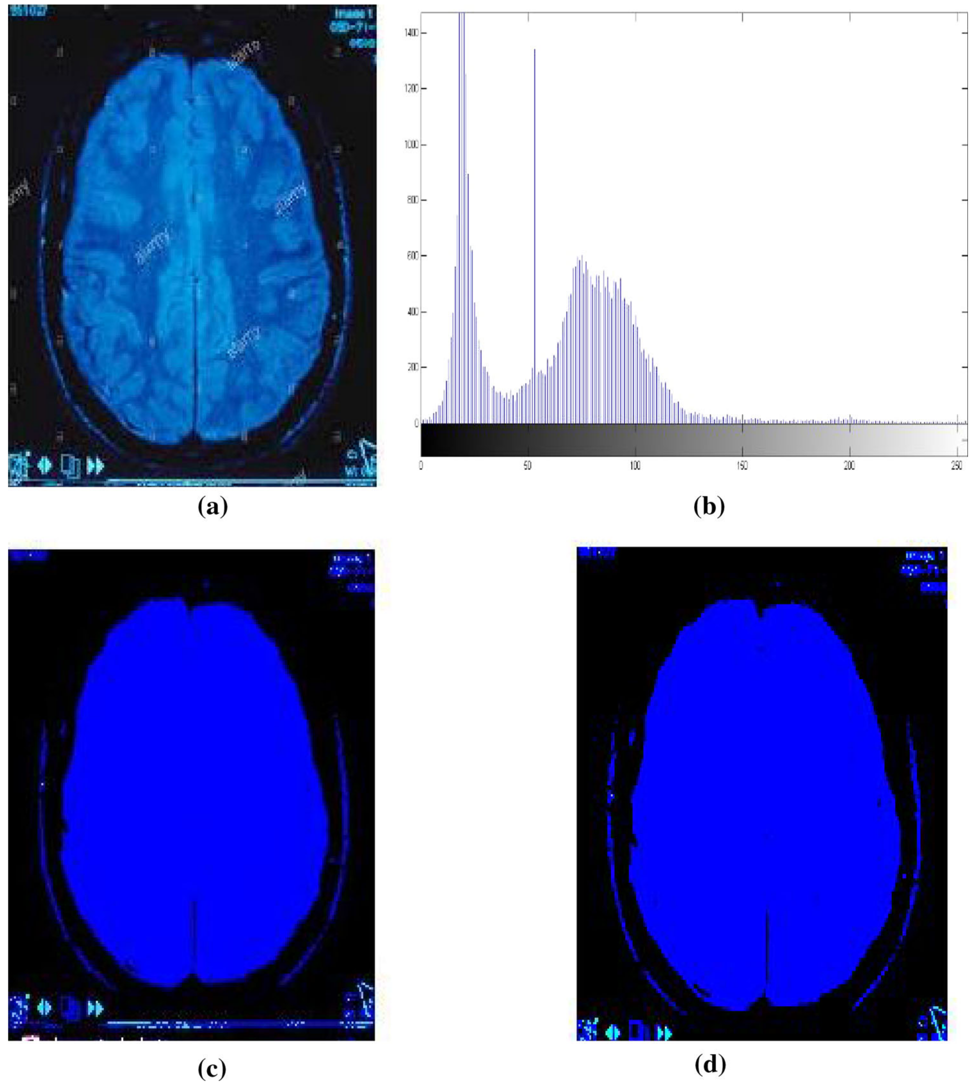
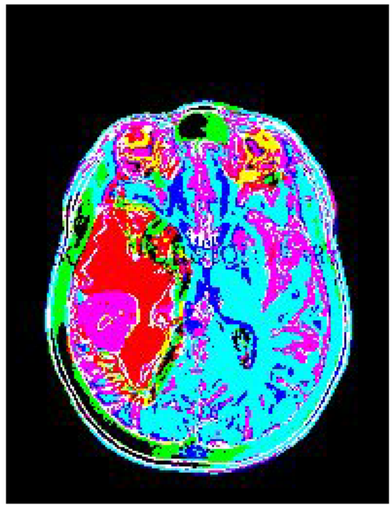


Fig. 4 Segmentation of image 3. **a** Original image, **b** histogram, **c** segmented image using Kapur's, **d** segmented image using TDE with Kapur's

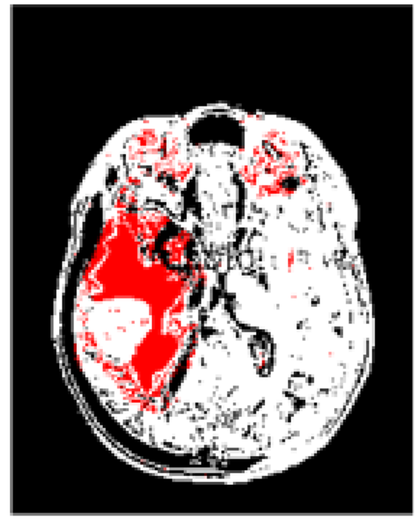
4 Conclusions

In this paper, TDE approach was executed and results were compared to classical mutation approaches in DE. The relative study showed improved outcomes for TDE with respect to better NFE and CPU time utilisation. TDE was then applied to Kapur's multilevel thresholding technique. The thresholding outcomes were proved to be improved for TDE approach in judgement with traditional differential evolution technique. The threshold image was then segmented to display the regions of tumour. This study shows that TDE strategy achieves improved results in terms of image quality and CPU time when compared to other state of art approaches. By using this technique, the affected tumourous regions are displayed distinctly after segmentation. Presently, the strategy has been tested for segmenting MRI images. This technique can be extended to be applied on various types of medical images for texture enhancement, image analysis and in other image processing sections where it can add value to the end user.

Fig. 5 Segmented tumour regions from Images



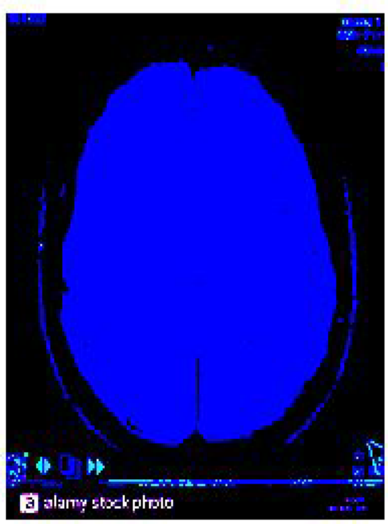
(a) Segmented Image 1



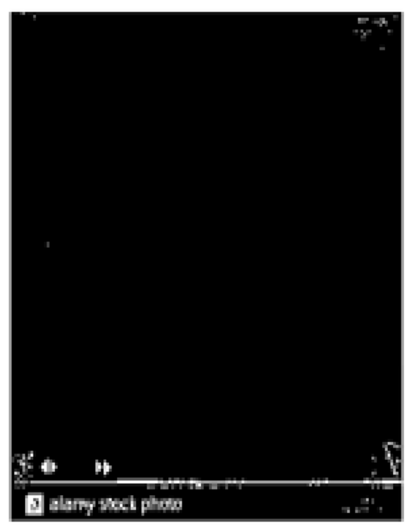
(b) Segmented tumour region from Image 1

(c) Segmented Image 2

(d) Segmented tumour region from Image 2



(e) Segmented Image 3



(f) Segmented tumour region from Image 3

Compliance with ethical standards

Conflict of interest The author(s) declare(s) that there is no conflict of interest.

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