ACEEE
Proc. of Int. Conf. on Advances in Computer Science, AETACS

An Automatic Medical Image Segmentation using Teaching Learning Based Optimization

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***Abstract*— Nature inspired population based evolutionary algorithms are very popular with their competitive solutions for a wide variety of applications. Teaching Learning based Optimization (TLBO) is a very recent population based evolutionary algorithm evolved on the basis of Teaching Learning process of a class room. TLBO does not require any algorithmic specific parameters. This paper proposes an automatic grouping of pixels into different homogeneous regions using the TLBO. The experimental results have demonstrated the effectiveness of TLBO in image segmentation.**

***Index Terms*— Evolutionary algorithm, population, Image segmentation, TLBO**

I. Introduction

Image segmentation is a process of dividing given image into a set of homogeneous groups. Image segmentation is a fundamental step in most of the image analysis applications. Clustering is an unsupervised classification method that classifies the given data set into groups of similar elements[1]. Many clustering algorithms are proposed in the literature as solutions to problem of image segmentation [2]. But almost all require some parameters in advance. There is a little work in automatic clustering. Thus finding optimal number of clusters and clustering structures automatically became a challenging task. Fogel et al and Sarkar,et al. have proposed an approach to dynamically cluster a data set using evolutionary programming, with two fitness functions one for optimal number of clusters and other for optimal centroids [3][4]. Lee and Antonsson used an evolutionary method to dynamically cluster a data set [5]. A unified algorithm for both unsupervised and supervised learning is proposed in 2002 [6]. Cheung was studied a rival penalized competitive learning algorithm that has demonstrated a very good result in finding the cluster number [7]. The algorithm is formulated by learning the parameters of a mixture model through the maximization of a weighted likelihood function. Swagatam Das and Ajith Abraham have proposed an Automatic Clustering using Differential Evolution (ACDE) algorithm[8]. Differential evolution (DE) is one of the most powerful stochastic real-parameter optimization algorithms in current use [9]. DE follows similar computational steps as in any standard evolutionary algorithm with specialized crossover and mutation operations [9]. Compared to other Evolutionary Algorithms DE is very simple to code. The recent studies on DE have shown that DE provides a better performance in very few compared to other algorithms. These features initiated researchers to provide more competitive solutions[10]. A Kernel-induced fuzzy clustering using Differential Evolution is proposed in 2010 [11]. Sanghamitra Bandyopadhyay and Sriparna Saha proposed evolution of clusters using point symmetry method. They have used a point symmetry based cost function as objective function [12]. A pixel wise fuzzy clustering is proposed to determine clusters automatically using DE selecting XB-index and

DOI: 02.AETACS.2013.4.99
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PS-measure as the objective functions [13]. Teaching Learning Based Optimization is a very recent population based evolutionary algorithm [14]. Rao and Patel have introduced the Teaching-Learning-Based Optimization (TLBO) algorithm which does not require any algorithm specific parameters. TLBO is developed based on the natural phenomena of teaching and learning process of a class room. TLBO contains two phases as teacher phase and learning phase [15]. As in any population based algorithms the TLBO is also contains population. Solution vectors are the learners and dimensions of each vector is termed as subjects. Best learner in the population is a teacher. This paper proposes an automatic clustering algorithm using TLBO that determines homogeneous groups automatically from grey image datasets. Experimental results on various images have shown the accuracy and efficiency of TLBO in image segmentation. Methodology is included in Section II, Experimental results are provided in Section III and Conclusions are presented in Section IV.

I. METHODOLOGY

The paper is mainly focused on the applicability of TLBO in finding optimal clusters automatically. The following subsections contain the procedure of TLBO and the proposed Automatic Clustering using TLBO (AUTOTLBO). The chromosome contains *inpk*, threshold values for active centroids and *inpk* centroids as in ACDE.

TLBO

TLBO is a recent evolutionary algorithm which providing competitive solutions for various applications and does not require any program specific parameters compared to other existing evolutionary algorithms. The process of TLBO is as follows

Initialization

The population X, is randomly initialized by a given data set of n rows and d columns using the following equation.

$$X_{i,j}(0) = X_j^{\min} + rand(1) * \left(X_j^{\max} - X_j^{\min}\right) \qquad (1)$$

$X_{i,j}$ Creation of a population of learners or individuals. The *i*[th] learner of the population X at current generation t with d subjects is as follows,

$$X_i(t) = \left\lfloor X_{i,1}(t), X_{i,2}(t), ..., X_{i,d}(t) \right\rfloor \qquad (2)$$

Teacher phase

The mean value of each subject, j, of the population in generation t is given as

$$M(t) = [M_1(t), M_2(t), ..., M_d(t) \qquad (3)$$

The teacher is the best learner with minimum objective function value in the current population. The Teacher phase tries to increase the mean result of the learners and always tries to shift the learners towards the teacher. A new set of improved learners can be generated by adding a difference of teacher and mean vector to each learner in the current population as follows.

$$X_i(t+1) = X_i(t) + r * (X_{best}(t) - T_F M(t)) \qquad (4)$$

TF is the teaching factor with value between 1 and 2, and riis the random number in the range [0, 1]. The value of TF can be found using the following equation (5)

$$T_F = round(1 + rand(1)) \qquad (5)$$

Learner phase

The knowledge of the learners can be increased by the interaction of one another in the class. For a learner, i, another learner is selected, j, randomly from the class.

$$X_i(t+1) = \begin{matrix} X_i(t) + r*(X_i(t) - X_j(t)) iff((X_i(t)) < f(X_j(t)) \\ X_i(t) + r*(X_j(t) - X_i(t)) iff((X_j(t)) < f(X_i(t)) \end{matrix} \qquad (6)$$

The two phases are repeated till a stopping criterion has met. Best learner is the best solution in the run.

Stopping criteria

The stopping criteria in the present work is "Stop by convergence or stagnation". The convergence of the algorithm is based on the fitness value of the fittest individual. The difference of fitness value of fittest individuals in any two successive generations is less than 0.0001, is the stopping

B. Automatic Clustering Using Tlbo (Autotlbo).

The new AUTOTLBO is to find optimal clusters automatically. Any cluster validity measure can be selected as fitness function. Here, CS Index is selected as fitness function [8]. The algorithm for the AUTOTLBO is as follows. Let X is a given data set with n, elements.
Step 1) Initialize each learner to contain Maxk, maximum number of randomly selected cluster centers and Maxk (randomly chosen) activation thresholds in [0, 1]. Learner is represented in the following figure figure1.

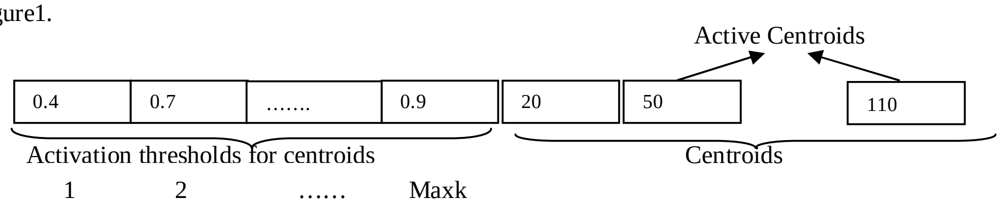


Figure1. Learner Representation

Step 2) Find the active cluster centers with value greater than 0.5,in each learner.
Step 3) For t = 1 to tmax do
- a) For each data vector Xp, calculate its difference from all active cluster centers.
- b) Assign Xp to closest cluster
- c)Evaluate each learner quality and find Teacher, the best learner using CS Index.
- d) Update the learners according to the TLBO algorithm described in the section 2.1.

Step 4) Report the final solution obtained by the globally best learner (one yielding the highest value of the fitness function) at time t = tmax.

C. Cluster validity measures [8].

Assessing the clustering results and interpreting the clusters found are as important as generating the clusters. Cluster Validity is the procedure of evaluating, quantitatively, the results of a clustering algorithm. Cluster validity indices correspond to the statistical– mathematical functions used to evaluate the results of a clustering algorithm on a quantitative basis. Using Internal Criteria, we are going to verify whether the clustering structure produced by a clustering algorithm fit the data, but using only information inherent to the data set.

CS Index

Chou *et al*. have proposed the CS measure for evaluating the validity of a clustering scheme. The centroid of a cluster is computed by averaging the elements that belong to the same cluster using

$$\vec{m}_i = \frac{1}{N_i} \sum_{X_j \in C_i} \overline{X}_j$$

$$CS = \frac{\sum_{i=1}^{k} \left[\frac{1}{N_i} \sum_{\vec{X}_i \in C_i} \max_{\vec{x}_q \in C_i} \{ d(\overline{X}_i, \vec{X}_q) \} \right]}{\sum_{i=1}^{k} \left[\min_{j \in k, j \neq i} \{ d(\vec{m}_i, \vec{m}_q) \} \right]}$$

CS measure is a function of the ratio of the sum of within-cluster distance to between-cluster distance. The cluster configuration that minimizes CS is taken as the optimal number of clusters, k.

Dunn index

The Dunn index defines the ratio between the minimal intra-cluster distance to maximal inter-cluster distance.
The index is given by:
D = dmin / dmax ,

Where, dmin denote the smallest distance between two objects from different clusters, and dmax the largest distance of two objects from the same cluster. The Dunn index is limited to the interval [0, 1] and should be maximized.

The Davies-Bouldin Index

The Davies-Bouldin index aims at identifying sets of clusters that are compact and well separated. The Davies-Bouldin validation index, DB, is defined as:

$$DB(X) = \frac{1}{k}\sum_{i=1}^{k} \max_{i \neq j}\left\{\frac{\Delta(C_i) + \Delta(C_j)}{D(C_i, C_j)}\right\}$$

Where, $D(C_i, C_j)$ defines the distance between clusters C_i and C_j (inter cluster distance); $\Delta(C_p)$ represents the intra cluster distance of cluster Cp, and k is the number of clusters of data set X. Small values of DB correspond to clusters that are compact, and whose centers are far away from each other. Therefore, the cluster configuration that minimizes DB is taken as the optimal number of clusters, k.

III. EXPERIMENTAL RESULTS

The AUTOTLBO performance is studied using two other Evolutionary algorithms Genetic Algorithm (GA), Differential Evolution, ACDE and with classical k-means algorithm. In the present work, population size is taken as 20. In the following tables first image is the original image, (a) is the output from k-means, (b) is the output generated by GA, (c) is from DE, output from ACDE provided as (d) and (e) is the segmentation result from the proposed AUTOTLBO algorithm. In each image, K-represents the number of clusters of the output image. In the images (d) and (e) the input number of clusters is specified as inpk. The segmentation results are validated using Dunn, DB, and CS clustering validity measures and the values are tabulated in Table 7.

TABLE I. SEGMENTATION RESULTS OF PEPPER IMAGE

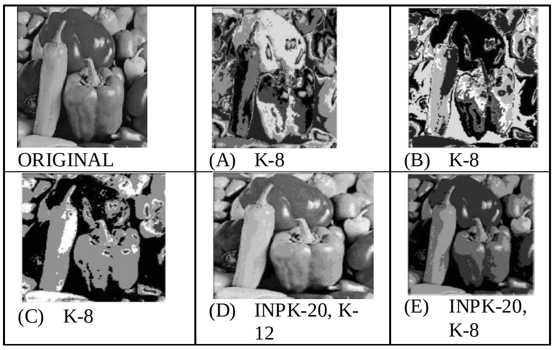


TABLE II. SEGMENTATION RESULTS OF BIRD IMAGE

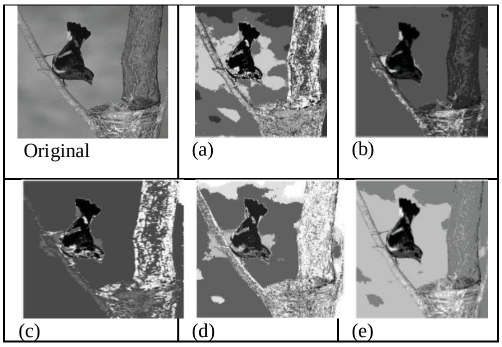


TABLE III. SEGMENTATION RESULTS OF LEENA

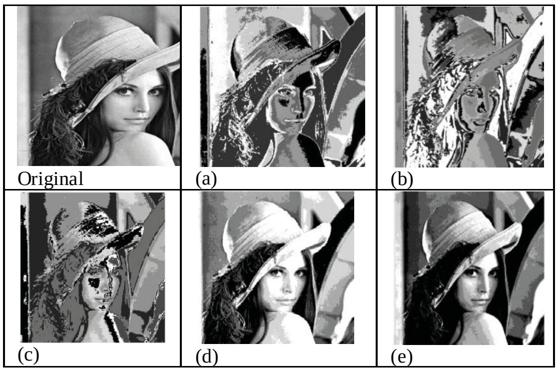


TABLE IV. SEGMENTATION RESULTS OF BEAR

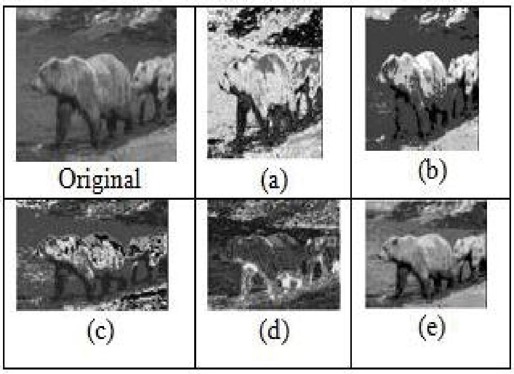


TABLE IV. SEGMENTATION RESULTS OF 3BIRDS

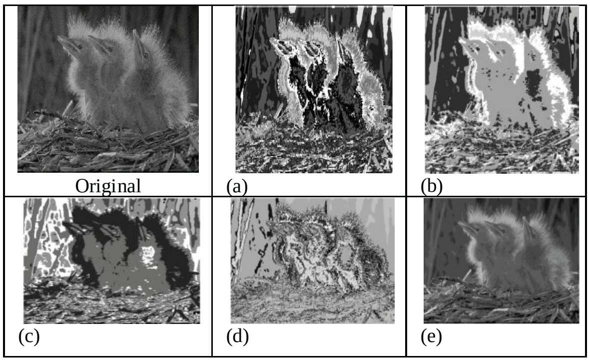


TABLE VI. SEGMENTATION RESULTS OF DOG

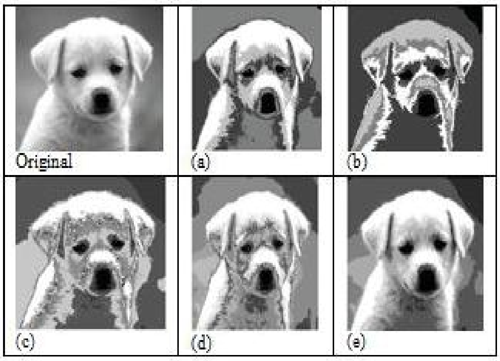


TABLE VII. VALIDITY MEASURES OBSERVED IN VARIOUS ALGORITHMS

		ACDE	DE	TLBO	AUTOTLBO	GA	kmeans
Pepper	cs	0.9268	**0.2939**	0.9805	0.9339	0.8487	0.7581
	db	0.5608	0.5570	0.5662	0.5887	0.5443	**0.5304**
	dunn	0.0323	0.0303	0.0333	0.0149	0.0127	**0.0370**
Leena	cs	**0.0050**	0.4450	1.2126	0.8277	1.1580	0.7223
	db	0.5872	0.5553	0.5123	0.5207	0.5530	**0.5116**
	dunn	**0.0357**	0.0263	0.0222	0.0175	0.0152	0.0333
Dog	cs	**0.1947**	0.6776	2.2213	0.7242	1.8319	0.7690
	db	0.5116	0.5362	0.6355	**0.4653**	0.6068	0.5626
	dunn	0.0286	0.0294	0.0222	0.0175	0.0156	**0.0345**
Bear	cs	**0.1730**	0.3369	1.2316	0.9266	1.1083	0.7705
	db	0.5148	0.5455	0.5568	0.5278	0.5334	**0.5136**
	dunn	**0.0370**	0.0333	0.0238	0.0175	0.0233	0.0303
3birds	cs	**0.0108**	0.3436	1.1633	0.8211	0.9646	0.6800
	db	0.7314	0.5127	0.5588	**0.5204**	0.5892	0.5333
	dunn	0.0303	**0.0357**	0.0192	0.0213	0.0145	0.0303
Bird	cs	**0.3102**	0.4057	1.2624	0.8378	1.2954	0.7549
	db	0.5539	0.5391	0.5084	**0.5168**	0.5759	0.5305
	dunn	**0.0417**	0.0313	0.0250	0.0154	0.0182	0.0250

Table1-6 shows the six original images and segmented portions of the images from various algorithms. The tables clearly show the efficiency of AUTOTLBO in segmenting the given images. Compared to DE the TLBO is very fast and simple. We have extended the concept of segmentation using TLBO to Medical imaging also. The results are tabulated in the following Table8. The values from AUTOTLBO are as equal as compared to the other methods.

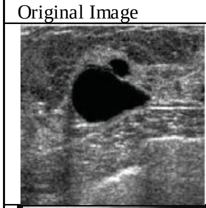
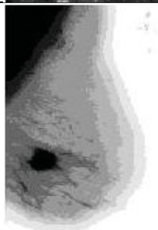
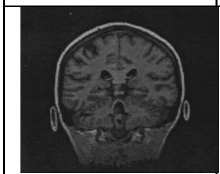
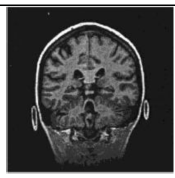
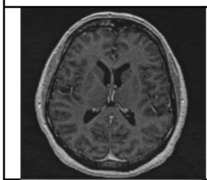
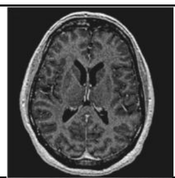
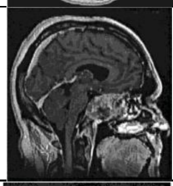
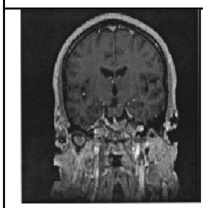
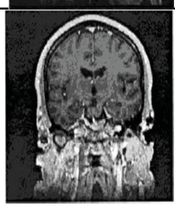
IV. CONCLUSIONS

TLBO is the very recent population based evolutionary algorithm that provided competitive solutions in mechanical engineering optimization. TLBO is very simple, fast, and doesn't required algorithm specific parameters. This paper proposes automatic clustering using TLBO for image segmentation. The performance of the proposed algorithm is studied by conducting tests on various images and the results are also compared with the existing evolutionary, classical, and automatic clustering techniques. The experimental results have shown in the accuracy and efficiency of AUTOTLBO in image segmentation. Successful image segmentation is also observed by AUTOTLBO in medical image segmentation.

ACKNOWLEDGMENT

This work was supported by grant from DST, New Delhi

TABLE VIII. SEGMENTATION RESULTS OF MEDICAL IMAGES

Original Image	AUTOTLBO image	Comments
		For the given 20, 8 segments are identified. Shape of breast cancer tissue has been correctly segmented.
		Breast mammogram
		Coronol section of human head
		Horizontal head section
		The cortex and the cerebellum are well segmented. In addition, the brainstem and the ventricle lying at the center of the brain are correctly separated
		Original gray-level image showing a coronal section of a human head. The entire brain is segmented as a region, as are the extracranial tissue and the neck muscle.

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