Unsupervised Optic Cup and Optic Disk Segmentation for Glaucoma Detection by ICICA

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***Abstract*—Glaucoma is an eye disease that can lead to vision loss by damaging the optic nerve. Although this disease can often be prevented with early glaucoma detection, lack of discernible early symptoms makes the diagnosis difficult. Measuring the cup-to-disc ratio (CDR) is a common approach for glaucoma detection. Glaucoma can be specified by thinning the rim area that identifies the CDR value. Clustering and image segmentation can simply divide fundus images into distinct areas to estimate the optic disc (OD) and the optic cup (OC). This paper is based on a robust method, using the improved chaotic imperialistic competition algorithm (ICICA) for determining the position of the OD and OC on color fundus images for glaucoma detection. The predicted OD and OC boundaries are then used to estimate the CDR for glaucoma diagnosis. The performance of the proposed method was evaluated by using the publicly available RIGA dataset. It was found that some of the common problems of K-means clustering algorithm can be addressed by the proposed method for achieving better results. Moreover, the OC and OD regions can be precisely separated from the color image so that ophthalmologists can measure OC and OD areas more accurately.**

***Index Terms*—Optic disc, Optic cup, Glaucoma detection, Improved chaotic imperialist competitive algorithm**

I. Introduction

Glaucoma is the second leading cause of blindness worldwide, almost 60 million cases reported worldwide in 2010, and an increase by 20 million is expected in 2020 [1], [2]. It is also the third cause of blindness in New Zealand [3]. If glaucoma leaves unnoticed, it can cause irremediable damage to the optic nerve leading to blindness [4]. Thus, diagnosing glaucoma at early stages is essential [2]. There are various types of glaucoma. Poor late prognosis of glaucoma causes vision loss.

In this paper, different types of glaucoma have been investigated which are defined by the appearance of changes in fundus images caused by various cases. One of the most important factors is the *intra-ocular pressure* (IOP) to resize *optic disc* (OD) and *optic cup* (OC); see Fig. 1. A localisation of the OD and OC (often the central part of the optic disc), and finding their borders, are performed by eye specialists where optic nerve tests include eye fundus examination. The presence of glaucoma can be identified by noticing optic nerve cupping, i.e. an increase of the OC in size [4]. One of the main indicators of the disease is the *cup-to-disc ratio* (CDR) between the sizes of the cup and the disc [2]. It is considered to be one of the most representative features of OD and OC areas for glaucoma detection, and, according to [10], an eye with a CDR of at least 0.65 is generally declared as being glaucomatous in clinical practice [4].

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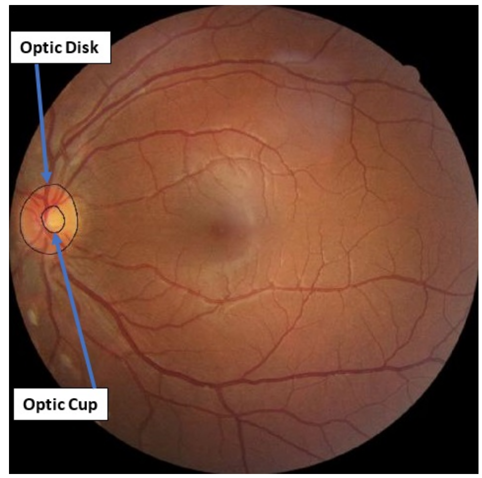


Fig. 1: The optic disk and optic cup as seen on a fundus image [11]

Clustering divides data into different clusters which are considered (e.g. by the applied algorithm) for being useful for object detection. Cluster analysis is the task of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups [6], [7]. It is a common technique for statistical data analysis, used in many fields such as machine learning, image analysis, pattern recognition, or medical imaging.

Clustering does not use category labels that tag objects with prior class labels; thus it is named *unsupervised learning* [8].

In this paper, we focus on partitional clustering and in particular, a popular partitional clustering method known as K-means clustering. The well-known K-means algorithm is one of the widely used algorithms due to its efficiency and simplicity in data clustering where it measures the distance between clusters representatives (centroids) and data points to partition data into K clusters. In most cases, the Euclidean distance is used as the dissimilarity measure. To find the best position of the representatives, the K-means algorithm minimizes the cost function of data variations around the centroids. However, the initial state may cause the algorithm to trap into a local optimum and as a result affects the quality of the final solution.

Recently, the use of meta-heuristic algorithms for solving the clustering problem has been successful in attracting more attention [5]. From the perspective of optimization problems, clustering can be considered as a specific type of NP-hard problems [9]. These types of algorithms involve search for finding an optimal solution for an optimization problem, with reducing the risk of being stuck in a local optimal region.

Motivated by the success of the *imperialist competitive algorithm* (ICA) with variant optimization problems, this paper proposes a novel data clustering algorithm based on an improved chaotic ICA for cluster analysis. The ICICA aims to enhance the capability of ICA in exploration without constraining its exploitation capabilities. In this paper, we integrate positive benefits of the chaos into ICA to enhance its performance. Proposed ICICA differs from the standard ICA in two important aspects: First, a special equation for assimilation mode is used to discard the local optima which provides better exploration opportunities for colonies. Second, in most of ICA implementations, an empire is collapsed and eliminated when it loses all of its colonies. Nevertheless, in this paper, we replace one of the weakest colonies of best empire (low cost) with this imperialist.

The reminder of this paper is structured as follows: Section II mention the public dataset that will be used in this research. Section III all steps of the methodology are explained such as preprocessing, K-means clustering and ICICA. Section IV results of ICICA algorithm which is applied to OC and OD detection, and section V concludes.

II. MATERIALS

The RIGA [11] dataset has been used in this research. The RIGA dataset includes three different types of files:

1) Some part of the MESSIDOR [12] database that contains 460 original fundus images with a resolution of $2,240 \times 1,488$.
2) The *Bin Rushd Ophthalmic Center* dataset which contains 195 original images with a resolution of $2,376 \times 1,584$.
3) The *Magrabi Eye Center* database that has 95 retinal images with a resolution of $2,743 \times 1,936$.

In total, there are 750 fundus images that are labeled manually by six ophthalmologists; thus, 4,500 manually marked images are available in RIGA. All images are saved in JPG and TIFF formats.

III. METHODOLOGY

The flow chart in Fig. 2 represents our suggested approach for OC and OD detection on fundus images based on the ICICA for glaucoma detection; the historic development of the ICICA is discussed below. The following sections explain the flowchart.

A. Pre-processing

First of all, detecting a *region of interest* ROI is an important part because this is here the area which should include OD and OC. In a pre-processing stage we consider it as being helpful to increase the quality (resolution) of the fundus images; this should precede the segmentation step.

In general, the pre-processing and enhancement stage is known as being essential for processing medical images. This stage is used to decrease image noise, highlight edges, and visualize digital images where needed. Examples of techniques also used in medical image pre-processing include *principle component analysis* (PCA) and superpixels before image segmentation. A subsequent enhancement stage includes an increase in image resolution or contrast enhancement for removing image noise.

A PCA grayscale method [15] has been used to enhance the quality of brightness when converting the given red-green-blue (RGB) input images into grayscale. A gamma filter is applied to have the best possible detection. Ideally, a given medical image should be sharp and balanced in brightness.

In this paper, noise is removed by using a median filter of size 11×11; due to this filter, intensity variance of light decreases in the fundus images, and this filter is also appropriate to maintain the shape of edges and edge locations.

Subsequent superpixel partitioning provides accurate boundaries between different tissues; after that, image features are extracted from each superpixel [14]. Using superpixels leads to improved accuracy and increases the speed of computation.

In this paper, superpixel segmentation is used to separate background regions in an image from the foreground, and for reducing the negative impacts of vessels in the segmentation's process. The RGB color space of the images, given prior to the PCA-grayscale transform, is mapped into an LAB space for better clustering. The use of the color-opponent LAB color space simplifies the separation of colors more approximate to human visual perception. We convert all fundus images from RGB into LAB color space.

Passing these stages, the fundus images are ready to be used in the clustering step.

B. K-Means Clustering Algorithm

K-means is a well-known clustering method that was primarily proposed by MacQueen and further developed by Hartigan and Wong [26]. K-means is an unsupervised learning algorithm in which the user divides the data (here we consider each data item as being a *pattern*) into a set of predetermined clusters. The clusters are defined by the use of patterns that identify the related clusters, and are regarded as being the centroids of the clusters.

For the given data set $\{x\} = \{x_1, ..., x_n\}$ of n patterns, a value $k > 0$ is specified, and k centers of k clusters (called the *centroids*) are, at first, determined randomly. These are the initial *seeds*.

Then, the set $\{x\}$ is divided into k clusters (i.e. subsets of patterns) such that each pattern is devoted to that cluster

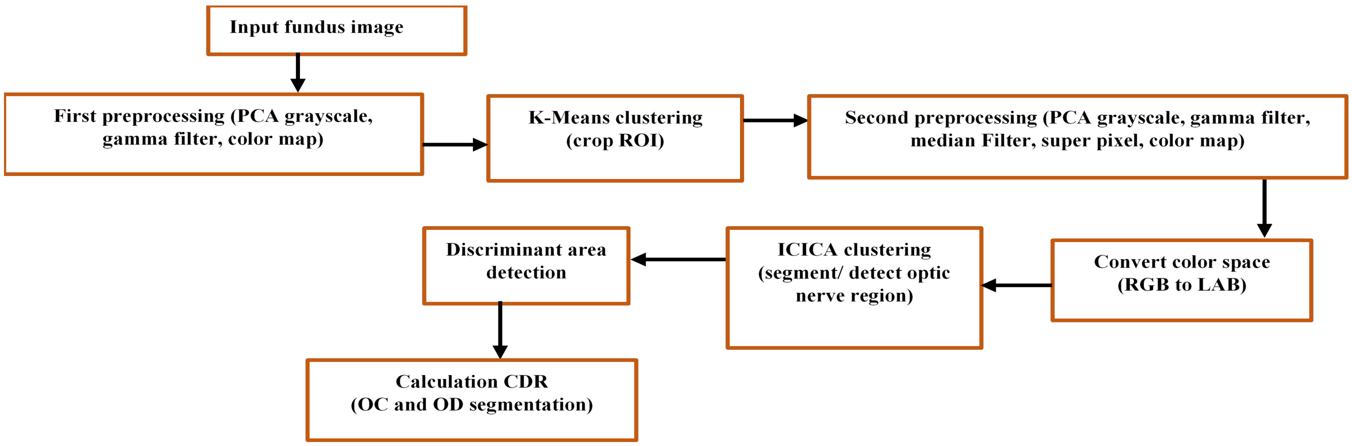


Fig. 2: Overall approach for fundus image for detecting OC and OD

where the center of this cluster has the closest distance to the considered pattern.

Then, considering all patterns devoted to the clusters, the position of the centers will be re-calculated, and the algorithm will continue this trend till no change (or "nearly no change") is made in the position of the centers. This means that all the patterns have converged into an "appropriate" cluster, and there is no further change in the clusters.

In this case, the objective function in Eq. (1) is a square-error function that defines the performance of the algorithm; it is applied for minimizing the following error term:

$$f = \sum_{i=1}^{k} \sum_{j=1}^{n} \|x_j - \mu_i\|^2 \tag{1}$$

where μ_i represents the center of the i^{th} cluster, and $\|x_j - \mu_i\|$ is the Euclidean distance of the j^{th} pattern from the center of the k^{th} cluster, for $j = 1, \ldots, n$ and $i = 1, \ldots, k$.

C. Imperialist Competitive Algorithm

The *imperialist competitive algorithm* (ICA) is one of the most recently developed meta-heuristic optimization algorithms that has been developed based on a socio-politically motivated strategy. The main idea behind this algorithm is to divide countries into two types, imperialistic countries and the colonies [9], [16]–[19].

Imperialistic competition and assimilation policy result in the convergence of colonies towards an optimal position. The efficiency of ICA as an excellent optimization method has been proved in various fields such as data clustering [21], hybrid flow scheduling problems [22], traveling salesman problems [23], skin color detection [24], multilayer perceptron weight optimization, and for artificial neural networks [25].

The ICA simulates a socio-political process of imperialism and imperialistic competition. This algorithm contains a population of agents or countries. Like other evolutionary algorithms, the ICA begins with a random primitive population in which each individual of the population represents a country. Countries in the ICA are similar to the chromosomes in a *genetic algorithm* (GA). At the initial stage, some of the best countries (less costly) are selected as imperial countries, and survivors are considered to be colonies of the imperialists [38].

Then colonies are divided between imperialists with regard to the power of the imperialists. After dividing all the colonies between the imperialist countries, the colonists move towards their related imperialists with regard to the cultural space. A collection of imperialist countries and some colonies make up an empire.

These empires compete with each other, and sometimes replace each other. The survival of an empire depends on its power and the way it controls its colonies against other rivals. The power of the larger empires increases with the collapse of smaller empires. As the result of the repetition of this competition among empires, the colonies' power comes close to the power of their imperialists, which is an indication of convergence. The upper limit of the imperialistic competition occurs when there remain only one imperialist and a number of colonies that are the closest colonies to the imperialist country with respect to position. The ideal situation is when colonies enjoy the same status and power as the imperialist.

D. Improved Chaotic Imperialist Competitive Algorithm

Chaos is one of the most important research achievements of nonlinear systems. A limited, unstable, dynamic behavior that is dependent and sensitive to initial conditions covers the infinite irregular periodic movements in the nonlinear systems. Although it appears to be random, it occurs in a definite nonlinear system in definite conditions [13], [26], [28], [29].

Many of the chaotic maps in the literature possess confidence, ergodicity, and random features and qualities. Instead of random sequences, chaotic sequences have been recently used for various applications due to their relatively good and very interesting results [31], [32]. They have also been used in association with some stochastic instead of exploratory optimization algorithms for the expression of optimization variables [33]–[35]. The selection of chaotic sequences are justified theoretically mainly due to their unpredictability feature, such as their wide range, irregularity, complex temporal behavior, and ergodic features and qualities.

In random-based optimization algorithms, the technique of using chaotic variables instead of random variables is called *chaotic optimization algorithm*. Optimization algorithms based on chaos theory [36] are random search methods that are different from swarm intelligence or any other existing evolutionary calculation methods. As chaos is not repeated, these methods do the total search with higher speed compared to random search that is dependent on probabilities.

When a random number is required in the ICA algorithm, it can be produced through the repetition of one stage of a selected chaotic map that is started from one of the random primary conditions in the first ICA repetition. Uni-dimensional irreversible maps are the simplest systems, possessing the ability of producing chaotic movements [37].

In the rest of this paper, we evaluate some of the famous uni-dimensional maps for glaucoma detection. In this paper, ICICA is proposed for the segmentation of the fundus images. The proposed technique uses the ability of the improved chaotic imperialistic competition algorithm, a meta-heuristic algorithm based on chaotic and imperialistic competition algorithm for the clustering and the detecting appropriate segmentation of the fundus images.

In 2012, Talatahari et al. [27] presented a chaotic imperialist competitive algorithm. This algorithm is formed by modifying the movement stage of the original algorithm. Considering the movement process of the ICA, by substituting the random numbers for the ICA parameters with sequences generated from chaotic systems. The algorithm not only uses different chaotic map values but also utilizes the orthogonal colony-imperialistic contacting line instead of θ for deviation of the colony as follows:

$$\begin{aligned} \{x\}_{new} = \{x\}_{old} + \beta \times d \times \{cm\} \otimes \{V_1\} \\ + cm \times \tan(\theta) \times d \times \{V_2\}, \\ \{V_1\} \, . \, \{V_2\} = 0, \| \{V_2\} \| = 1 \end{aligned} \quad (2)$$

where β is a parameter whose value is greater than 1 and d is the distance between the colony and the imperialist Fig. 3. $\{V_2\}$ is perpendicular to $\{V_1\}$, since this vector must cross the point obtained from the two first terms. $\{cm\}$ is a chaotic vector based on the selected map and the sign $\otimes$ denotes an element-by-element multiplication. However, in multi-dimensional problems like clustering, the calculation of $\{V_2\}$ is a very complicated task and is mathematically difficult.

Therefore, in this paper we change the movement step as follows:

- First, different chaotic map values are utilized for different components of the solution vector in place of only one value (2).
- Second, it is possible to obtain a random value for θ in third terms of the (2) that will be randomly changed in $(0, 1)$ at each iteration.

For a proper exploration and escape from local minima, the value of the selected chaotic map in (2) with initial random value is calculated in each iteration. The equation is modified by

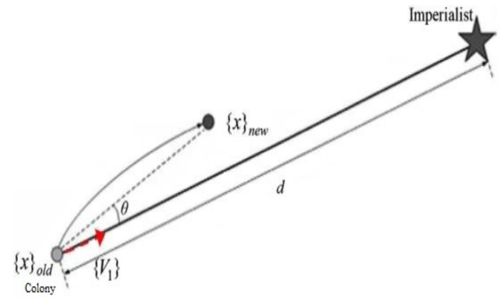


Fig. 3: Movement of colonies toward their relevant imperialists [27]

$$\begin{aligned} \{x\}_{new} = \{x\}_{old} + \beta \times d \times \{cm_k\} \otimes \{V_1\} \\ + \{cm_k\} \times \tan(\{\theta_k\}) \times d \end{aligned} \quad (3)$$

where in (3) $\{cm_k\}$ is the kth chaotic vector, $\{\theta_k\}$ is the kth vector of θ values that will be randomly in the range of $(0, 1)$ at each iteration.

Equation (4) of the circle map in chaotic map is as follows, and It is used to generate chaotic sequences that are required at each time of the algorithm. The random numbers are replaced by these chaotic sequences in the original imperialist competitive algorithm [30]:

$$X_{n+1} = X_n + b - \left(\frac{a}{2\pi}\right) \sin(2\pi X_n) \bmod (1) \quad (4)$$

Given $a = 0.5$ and $b = 0.2$, this chaotic map produces chaotic sequences in the interval $(0, 1)$.

IV. Experiments and results

The proposed algorithm was applied to the RIGA dataset while both color conversion and ICICA clustering techniques were used Fig. 4.

Moreover, the K-means algorithm was applied to the pre-processed images of fundus for comparison by calculating the *root mean square error* (RMSE) [39].

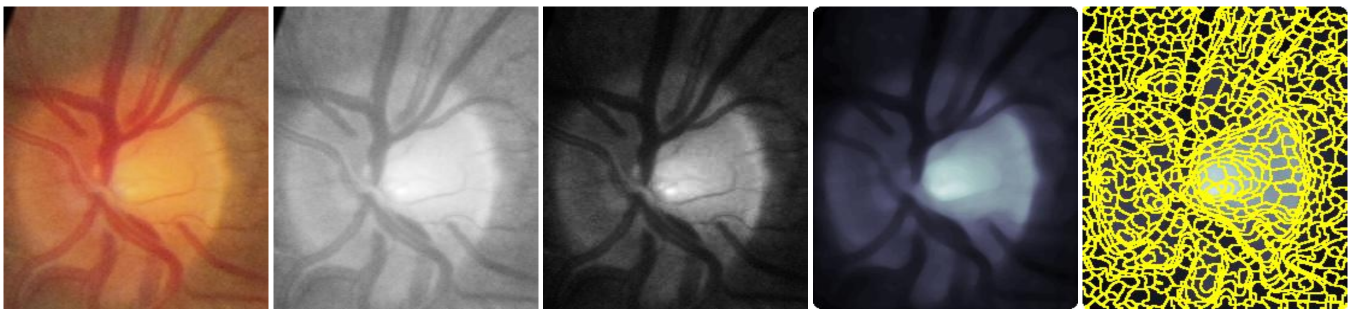
For extracting the ROI from fundus images, the lowest RMSE was selected to find the background by drawing a box around the center of the cluster Fig. 4d. Then, the ROI images were considered as input for the ICICA algorithm to extract the OD and OC.

Upon color transformation of images from gray level to RGB, and then to LAB color space, the ICICA was employed to cluster the input image and segment its pixels. However, the clustering may lead to the production of separate regions with black holes or dots. Furthermore, Otsuš model was applied to obtain the final segmented regions. The following test shows how the proposed algorithm was used to detect OD and OC on fundus images Fig. 5.

After transferring the original gray image to RGB and then to LAB color space, the approach produced three components

(a) input (b) remove background (c) PCA-grayscale (d) ROI (e) Ophthalmologist

Fig. 4: Preprocessing and extraction of a region of interest [11]



(a) ROI (b) Grayscale PCA on ROI (c) Gamma filter (d) Color map (e) Superpixel

(f) Output superpixel (g) OC cluster with ICICA (h) OD cluster with ICICA (i) Proposed method OC (j) Proposed method OD

Fig. 5: OC and OD detection results [11]

of “L” for light intensity, “A” related to the color distribution along the green-to-red axis, and finally “B” for color located along the blue-to-yellow axis. Therefore, all information related to color is located in “A” and “B” layers.

The difference between two colors can be measured through the measurement of their Euclidean distance. The ICICA clustering algorithm was used to classify color in the “A B” color space. This algorithm, like the K-means clustering, requires specification of a number of clusters and distance measurement criteria to detect the degree of closeness of objects together.

Given the fact that the information related to the existing color was located in the “A B” color space, the objects were pixels with “A” and “B” value that were classified in to three clusters by ICICA clustering algorithm and Euclidean distance metrics.

Figure 5 shows the results of applying the ICICA algorithm to the processed images and extracting the final results are shown in Fig. 5i and Fig. 5j as comparative performance evaluation.

The OD and OC regions were marked by ophthalmologist manually as shown in Fig. 4e. It should be noted that the RIGA database was annotated by six different ophthalmologists, which in most cases the decision had not been the same.

V. Conclusions

Image clustering is used to describe high level of image contents which plays an important role in solving pattern recognition problems and medical image processing.

An image segmentation method based on ICICA and color conversion techniques is proposed for segmentation of retina images. The presented evaluations on fundus images show encouraging results.

In order to achieve a better performance, after de-noising the images using the median filter and improving the quality of the image, the clean image was converted to RGB and then to the LAB color space. Then, the ICICA clustering algorithm was employed to cluster the images and label the pixels. Finally, the Otsu method was used to completely segment the OC and OD.

The proposed method avoids the common problems of k-means clustering algorithms, such as dependence on initial values and early convergence that cause poor results.

In order to evaluate the performance of the proposed method, the final results were compared with the results of K-means clustering using the RMSE parameter. According to the results, the OC and OD regions can be precisely separated from the color image and the proposed method enables ophthalmologists to measure OC and OD areas accurately.

References

[1] H. A. Quigley and A. T. Broman, "The number of people with glaucoma worldwide in 2010 and 2020," British J. Ophthalmology, 90(3): 262–267, 2006.

[2] A. Almazroa, R. Burman, K. Raahemifar, and V. Lakshminarayanan, "Optic disc and optic cup segmentation methodologies for glaucoma image detection: a survey," J. Ophthalmology, 42: 162–189, 2015.

[3] New Zealand: Latest stats at a glance 2015; see www.blindfoundation.org.nz

[4] A. Sevastopolsky, "Optic disc and cup segmentation methods for glaucoma detection with modification of U-Net convolutional neural network," J. Pattern Recognition Image Analysis, 27(3):618–624, 2017.

[5] S. J. Nanda and G. Panda, "A survey on nature inspired metaheuristic algorithms for partitional clustering," Swarm Evolutionary Computation, 16: 1–18, 2014.

[6] F. Li and R. Klette, "A variant of adaptive mean shift-based clustering," Springer, LNCS 5506, pp. 1002–1009, 2008.

[7] T. S. Madhulatha, "An overview on clustering methods," arXiv preprint, arXiv:1205.1117, 2012.

[8] A. K. Jain, "Data clustering: 50 years beyond K-means," Pattern Recognition Letters, 31(8):651–666, 2010.

[9] E. Falkenauer, "Genetic Algorithms and Grouping Problems," Wiley, New York, 1998.

[10] M. U. Akram, A. Tariq, S. Khalid, M. Y. Javed, S. Abbas, and U. U. Yasin, "Glaucoma detection using novel optic disc localization, hybrid feature set and classification techniques," Australasian Physical Engineering Sciences Medicine, 38(4):643–655, 2015.

[11] A. Almazroa, S. Alodhayb, E. Osman, E. Ramadan,M. Hummadi, M. Dlaim, M. Alkatee, K. Raahemifar, and V. Lakshminarayanan, "Retinal fundus images for glaucoma analysis: the RIGA dataset," Proc. SPIE Int. Symp. Medical Imaging, vol. 10579, p. 8, 2018.

[12] E. Decenciére, X. Zhang, G. Cazuguel, B. Lay, B. Cochener, C. Trone, P. Gain, R. Ordonez, P. Massin, and A. Erginay, "Feedback on a publicly distributed image database: the Messidor database," Image Analysis Stereology, 33(3):231–234, 2014.

[13] W. M. Zheng, "Kneading plane of the circle map," Chaos Solitons Fractals, 4(7):1221–1233, 1994.

[14] M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T. L. Jones, T. R. Barrick, F. A. Howe, and X. Ye, "Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in FLAIR MRI," Int. J. Computer Assisted Radiology Surgery, 12(2):183–203, 2017.

[15] T. Coye, "A novel retinal blood vessel segmentation algorithm for fundus images," MATLAB Central File Exchange, 2016.

[16] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition," Proc. IEEE Congress Evolutionary Computation, pp. 4661–4667, 2007.

[17] E. Atashpaz-Gargari and C. Lucas, "Designing an optimal PID controller using colonial competitive algorithm," Proc. Iranian Joint Congress Fuzzy Intelligent Systems, 2007.

[18] E. Atashpaz-Gargari, F. Hashemzadeh, R. Rajabioun, and C. Lucas, "Colonial competitive algorithm," Int. J. Intelligent Computing Cybernetics, 1(3):337–355, 2008.

[19] E. Atashpaz-Gargari, F. Hashemzadeh, and C. Lucas, "Designing MIMO PIID controller using colonial competitive algorithm: Applied to distillation column process," Proc. IEEE Congress Evolutionary Computation, pp. 1929–1934, 2008.

[20] A. Jasour, E. Atashpaz-Gargari, and C. Lucas, "Vehicle fuzzy controller design using imperialist competitive algorithm," Proc. Iranian Joint Congress Fuzzy Intelligent Systems, 2008.

[21] T. Niknama, E. T. Fard, N. Pourjafarian, and A. Rousta, "An efficient hybrid algorithm based on modified imperialist competitive algorithm and K-means for data clustering," Engineering Applications Artificial Intelligence, 24(2):306–317, 2011.

[22] J. Behnamian and M. Zandieh, "A discrete colonial competitive algorithm for hybrid flowshop scheduling to minimize earliness and quadratic tardiness penalties," Expert Systems Applications, 38(12):14490–14498, 2011.

[23] M. Yousefikhoshbakht and M. Sedighpour, "New imperialist competitive algorithm to solve the travelling salesman problem," Int. J. Computer Mathematics, 90(7):1495–1505, 2013.

[24] N. Razmjooy, B. S. Mousavi, and F. Soleymani, "A hybrid neural network imperialist competitive algorithm for skin color segmentation," Mathematical Computer Modelling, 57(3-4):848–856, 2013.

[25] M. Tayefeh Mahmoudi, N. Forouzideh, C. Lucas, and F. Taghiyareh, "Artificial neural network weights optimization based on imperialist competitive algorithm," Proc. Int. Conf. Computer Science Information Technology, pp. 244–247, 2009.

[26] J. MacQueen, "Some methods for classification and analysis of multivariate observations," Proc. Berkeley Symp. Mathematical Statistics Probability, 1(14):281–297, 1967.

[27] S. Talatahari, B. Farahmand Azar, R. Sheikholeslami, and A. H. Gandomi, "Imperialist competitive algorithm combined with chaos for global optimization," Communications Nonlinear Science Numerical Simulation, 17(3):1312–1319, 2012.

[28] D. Yang, G. Li, and G. Cheng, "On the efficiency of chaos optimization algorithms for global optimization," Chaos Solitons Fractals, 34(4):1366–1375, 2007.

[29] L. M. Pecora and T. L. Carroll, ' 'Synchronization in chaotic systems," Physical Review Letters, 64(8):821–824, 1990.

[30] R. M. May, "Simple mathematical models with very complicated dynamics," Nature, 261(5560):459–67, 1976.

[31] M. Suneel, "Chaotic sequences for secure CDMA," arXiv Preprint nlin/0602018, pp. 6–9, 2006.

[32] X. Zhang and W. Chen, "A new chaotic algorithm for image encryption," Proc. Int. Conf. Audio Language Image Processing, 29:889–892, 2008.

[33] B. Alatas, "Chaotic bee colony algorithms for global numerical optimization," Expert Systems Applications, 37(8):5682–5687, 2010.

[34] R. Caponetto, L. Fortuna, S. Fazzino, and M. G. Xibilia, "Chaotic sequences to improve the performance of evolutionary algorithms," IEEE Trans. Evolutionary Computation, 7(3):289–304, 2003.

[35] B. Alatas, E. Akin, and A. B. Ozer, "Chaos embedded particle swarm optimization algorithms," Chaos Solitons Fractals, 40(4):1715–1734, 2009.

[36] L. dos Santos Coelho and V. C. Mariani, "Use of chaotic sequences in a biologically inspired algorithm for engineering design optimization," Expert Systems Applications, 34(3):1905–1913, 2008.

[37] E. Ott, "Chaos in Dynamical Systems," second edition, p. 478, 2002.

[38] S. Hosseini, and A. Al Khaled, "A survey on the imperialist competitive algorithm metaheuristic: Implementation in engineering domain and directions for future research," Applied Soft Computing, 24:1078–1094, 2014.

[39] J. Kaur, S. Agarwal, and R. Vig, "A methodology for the performance analysis of cluster based image," Int. J. Engineering Research Application, 2(2):664–667, 2012.