Coyote Optimization Algorithm based Multilevel Thresholding Approach for Image Segmentation

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Abstract: Multilevel image thresholding is a process that is important to divides a gray level image into a number of different parts. This method determines more than one threshold for a provided image and divides the image into a few bright areas that equivalent with a background as well as multiple objects. Classic technique for multi-level thresholding has optimization problem and high computational costs. To deal with the problem, metaheuristic methods are broadly used in this area of research to find optimal thresholds. This manuscript, we propose a coyote optimization algorithm for the biologically inspired algorithm for multi-level thresholding. The COA also gives novel methods to balance studio exploitation on maximization process. COA contributes with a new method of setup and balancing instructions exploration and exploitation in the optimization problem. COA performance is assessed in 40 reference functions by different characteristics, such as diversity, segmentation and number of optimal variables. As test results substantially show the advantage of our technique objective functions value, image quality measures, and convergence performance.

1. INTRODUCTION

Multilevel thresholding is an essential method to partitioning images with more attention in the last few years. That plays an important role on image processing. Between all famous segmentation methods, threshold is the major techniques employed. In digital image processing, threshold denotes simplest technique of segmenting images. As grayscale image, the threshold may be employed to make binary images. Simplest threshold techniques restore every pixel on image through black pixel if the intensity of image is fewer to some constant T or a white pixel if the intensity of the image is higher to some constant. At an instance image on right, this causes the dark tree to become fully black as well as white snow to fully white. If the image is easily divided into two cases, it is referred as two-level threshold. Multilevel thresholding is a process, which segments a gray level image into various dissimilar regions. This method decides more than one threshold of provided image as well as segments the image into some regions of brightness that match to a background and a variety of objects.

Multi-level threshold is considered an optimization issue. This is an essential and demanding task of traditional complete systems as their large computational costs. Like,
meta-heuristic techniques have collective much concern in latest years. Many of the relevant work include entropy of histogram [1], image transformation (IT) [2], elephant herding optimization (EHO) [3], hybrid differential evolution (HDE) [4], Grey Wolf Optimizer (GWO) [5], Shannon and Fuzzy entropy (SFE) [6], Levy flight firefly (LFF) [7], Human mental search (HMS) [8], Whale Optimization Algorithm (WOA) [9], Backtracking search algorithm (BSA) [10], Oppositional symbiotic organisms search (OSOS) [11], nature inspired optimization (NIO) [12], animal migration optimization algorithm (AMO) [13], Hybrid Salp Swarm Algorithm and Fuzzy Entropy [14], Two-dimensional multilevel threshold (TDMT) [15], Crow Search Algorithm (CSA) [16], Beta differential evolution (BDE) [17], bacterial foraging optimization (BF) [18], Krill Herd Optimization (KHO) [19], Hybrid Harris Hawks Optimization (HHHO) [20].

In this thesis, new meta-heuristics for universal optimization referred as Coyote Optimization Algorithm (COA) is projected, it also excited to the alive Canislatrons mostly North America. Consider a designed mechanism social structure of coyote as well as their adaptation a different mechanism with the environment and it contributes the structure of meta-heuristics from the literature. That too provides new methods for balancing the study exploitation in maximization procedure.

COA is estimated beneath a place of actual parameters accepted the main functions of boundary control Institute of Electrical and 2005 and 2015 competitions Evolutionary Computation of Electronics Engineers Congress(IEEE-CEC), and its accomplishment is equated from literature to another bio-inspired meta-heuristics. Comparative statistical testing is used to assess significance the outcomes get as well as effectiveness of proposed COA.

Rest of this manuscript is systematic from below. Section 2 describes a COA, when Section 3 suggests a definitions fundamental of proposed algorithm. Next, Section 4 shows computational outcomes imitation as well as their Statistical Analysis. At last, Section 5 concludes the manuscript.

2. RELATED WORKS

S. Sarkara et al. developed a multi-level image thresholding that employs a combination of Differential Evolution (DE) and Renyi entropy [21] algorithm. This model propose a new approach to the unsupervised classification of terrain analysis of hyper-spectral satellite images to enhance the splitting among objects as well as background through utilizing a multi-level threshold depend on maximal Renyi entropy (MRE). Multi-level thresholding that divides a gray-level image as various different homogeneous areas denotes broadly famous tool to split. Regardless, the use of multi-level threshold in difficult applications such as hyper-spectral image analysis has not yet been investigated. Differential evolution (DE), easy and methodical evolutionary method of modern interest, used to enrich computational time as well as robustness of projected algorithm. DE activities are completely researched by correlating it through other well-known nature-inspired global optimization methods.

Multi-level image threshold utilizing Otsu as well as chaotic bat algorithm [22] was developed by S.C. Satapathy. The Advanced Harris Hawks Optimizer (HHO) used to overcome global optimization as well as decide ideal threshold values of multi-level image segmentation issues. HHO denotes novel swarm-based metaheuristic method, which assumes character of Harris Hawks throughout the entire rabbit-catching procedure. HHO recognized its robust activities from swarm-based optimization method. In any case, the population-based HHO may remain face few drawbacks when it comes to multimodal as well as compound issues. For instance, this optimizer can be stuck with local optima as well as shift toward mature integration while exploration and exploitation phases are performed to alleviate such deficiencies, advanced HHO is suggested, which assumes Sulfur Swarm Algorithm (SSA) from competitive technique of improving the balance among their exploration and exploitation trends. First, a solution set is created. We then split those solutions into two parts, HHO exploration and exploitation phases are used in the first half, and SSA search conditions are utilized to upgrade the solutions on second half. Subsequently, better solutions as union sub-population are chosen to go on the implementation procedure. Due to Advanced HHO, also known as HHOSSA, the effectual multi-stage image segmentation method has been evolved at this investigation. An exhaustive place of tests is carrying out as 36 IEEE CEC 2005 reference functions as well as 11 natural grayscale images.

H. Liang et al. developed a multi-level image thresholding depend on grasshopper optimization algorithm (GOA) [23]. Right now, the modified Locust Optimization Algorithm (GOA) accomplished to form a very realistic multi-level challenge cross entropy as well as minimize problem. Levy flight method is used to deplane real GOA as well as coherence GOA exploration as well as exploitation. The Chalice entropy technique is developed for their efficiency as well as ease. Even though it is well-organized and provides a good outcome at a two-stage threshold, its evaluation is complicated while count of thresholds maximizes. Experiments are conducted between the five sophisticated metaheuristic algorithms and the scheduled ones. Furthermore, counseled method is equated by threshold methods with respect to the class variation technique (Otsu) as well as renyi entropy function. Real-life as well as plant stomata images are employed on examines to test potency of related algorithms.

I. G. Schaefer et al. were developed multi-level image thresholding model that utilizes the Benchmarking of Population-Based Meta-heuristic algorithm [24]. The image is divided into non-overlapping areas rated in image
histogram. Conventional methods of multilevel imaging thresholds are time absorbing. It’s particularly true while the thresholds count is augmented by curse of the dimension, search space elaborates aggressively from parameters (thresholds) increase. One method for solving this issue is to use population-based metaheuristic algorithms. Now evaluated the implementation of 13 population-based algorithms on large-dimensional multilevel image threshold search intervals, as several of these optimization algorithms are presented in the literature. Whale Optimization Algorithm, Gray Wolf Optimizer, Crane Optimization Instruction, Biogeography Based Optimization, Teaching-Learning-Based Optimization, Gravity Search Algorithm, Imperial Competitive Instruction, Crane Search, Firefly Algorithm, Bad Algorithm, Differential Evolution, Particle Swarm Optimization, as well as Genetic Instruction.

W. Tang developed a multilevel image threshold that uses the combination of minimal cross entropy as well as alternating direction multiplier technique [25]. In multi-level image threshold, they motivate the topic of rapid color image division and suggest a two-stage image separation technique that uses a multi-stage threshold algorithm as well as statistical area merger method (SRM). Through the support of Alternative Amplifier Direction, exact threshold values may be decided through intersection of image histogram subsystems, which go after the minimal cross entropy (MEC). At second step, the adapted SRM is employed to eliminate parts of the threshold image that are unreasonably separated to bring the final outcomes.

T.R Farshi and M.Orujpour approach was motivated and designed using the social spider algorithm [26] of global optimization. The Maximum Variation technique (Otsu) is best known and broadly utilized methods throughout partitioning. Apart from that Otsu be used for a two-level threshold, it can also be elaborated to a multi-level image threshold. Identifying perfect threshold values on multi-level folder denotes time consuming procedure and therefore the optimization algorithm defeats a problem. Now study, the social spider algorithm of global optimization is employed to buildup the variance among classes to perform multi-level image constraints. Now, the social spider algorithm of universal improvement is used to increase the contrast between classes to accomplish multi-level image limitations.

The multi-level image thresholding is depends on Otsu’s model [27] developed by M.H. Merzban and M. Elbayoumi. Gray image denotes fundamental functions of computer perception, by request on image refinement as well as partition in multi-level threshold. Distinct criteria for choosing threshold values have been planned. One of the guideline is Otsu criterion, which uses the greatest deviation approach among classes. While using a multi-stage threshold for an image is a straightforward function, the Otsu criterion with the threshold of estimation denotes calculation premium procedure. Now, we review dynamic programming algorithms, which maintain a correct as well as systematic solution towards issues, as well as contrast it by latest meta-heuristic algorithms. We sustain a proper evidence of perfection of an algorithm. Calculation cost of the algorithm is direct under count of threshold levels.

### Multi-level Thresholding

This section assesses the multilevel threshold issue. The threshold denotes histogram [1] of image as well as optimal thresholds are usually found at different valley histogram. Though, valleys can be difficult to find. Histogram can contain numerous high peaks as well as valleys. One of the most popular methods is the Otsu technique [27], it overwhelm this issues. It works on foundation of pixel probability histogram.

I have specified you an image of the size of N gray in the range [0, N - 1], pixels count in position y indicates as $n_y$, as well as total pixels count as $L = l_0 + l_1 + ... + l_{N-1}$.

Therefore, gray level probability is definite by $P_y$ is,

$$P_y = \frac{n_y}{L}$$

(1)

Suppose there are K threshold, $t_1, t_2, ..., t_v$ any division of provided image gray levels in $v + 1$ classes are: $C_0 \text{ for}[0, t_1 - 1], C_1 \text{ for}[t_1, t_2 - 1], ..., C_v \text{ for}[t_v, N - 1]$ where $t_1 < t_2 < ... < t_v$.

After that, with $t_0 = 0$ and $t_{v+1} = N$, Class means levels $\mu_v$, class event probabilities $\omega_v$ the total mean position $\mu_S$ of the original image is calculated (2), (3) and (4) respectively

$$\mu_v = \sum_{x=t_v}^{t_{v+1}} xP_x / \omega_v$$

(2)

$$\omega_v = \sum_{x=t_v}^{t_{v+1}} P_x$$

(3)

$$\mu_S = \sum_{x=0}^{N-1} xP_x$$

(4)

The objective function is computed from below:

$$Fit = \sum_{v=0}^{V} \omega_v (\mu_v - \mu_S)^2$$

(5)

The Otsu multi-level threshold issue is defined from below:

$$\{t_1^{*}, t_2^{*}, ..., t_v^{*}\} = \arg \max \{Fit(t_1, t_2, ..., t_V)\}$$

(6)
3. FUNDAMENTALS OF PROPOSED ALGORITHM

The proposed Coyote Optimization Algorithm (COA) is a population-based algorithm [24] stimulated by Canis latrans species classified from swarm intelligence as well as evolutionary heuristics and inspired through behavior of coyotes. At disparity through Gray Wolf Optimizer (GWO) [5] that outstands in Canis lupus species, COA consists of distinctive algorithmic structural configuration and is not focused at social hierarchy as well as rules of domination of such animals, despite that alpha participates from leader of package (described later). Additionally, COA focuses on social structure as well as skill coyotes face as an alternative to hunting prey only as it evolves on GWO [5].

At COA, coyote population is partitioned into $N_m \in N^*$ packs with $N_n \in N^*$ every coyotes. At initial proposal, coyotes count per packet denotes static as well as equal for entire packets. Therefore, total population on algorithm is get through multiplication for $N_m$ and $N_n$. For simplification causes, solitary (or transient) coyotes may not measure at initial version of algorithm. For facilitating a reader’s sympathetic, every coyote denotes probable solution of optimization issue as well as their social condition denotes objective function cost.

Based on, intrinsic factors (sex, social Level as well as packed as a member of the coyote) and exterior Such as ice depth, snowfall hardness, temperature and dead bio) are indicates as impacts in which coyote activities. Hence, the COA mechanism Designed based on social conditions Coyotes, i.e. global decision variables $a \rightarrow$ Optimization problem. Thus, social status is a social (synthesis) End variables $n^{th}$ coyote of $m^{th}$ pack in $t^{th}$ Written as the instant of time.

$$soc_{n,t} = \{a_1, a_2, .., a_D\}$$

(7)

It involves on coyote’s adaptation toward surroundings (objective function cost. $fit_{n,m,t} \in R^*$

The initial step in COA for initializing coyotes world population. Since COA denotes stochastic algorithm, first social conditions are established randomly of every coyote. It occurs through conveying random values within the search space of $n^{th}$ coyote for $m^{th}$ pack of $t^{th}$ dimension package, from below:

$$soc_{n,m,t} = lb_i + r_i(ub_i - lb_i)$$

(8)

In which $lb_i$ and $ub_i$ are under and $i^{th}$ upper boundaries for decision variable, D denotes search space dimension as well as $r_i$ denotes actual random number within range of [0,1] utilizing uniform probability. Thereafter, Coyote’s adaptation to its current social conditions rated:

$$fit_{n,m,t} = f(soc_{n,m,t})$$

(9)

Initially, coyote is arbitrarily allocated toward packages; though from time to time leave its packet behind Join alone or in package. The Coyote discharge as set in terms of coyotes count within the packet as well as the probability that $p_j$ will occur is,

$$p_j = 0.005.N_n^2$$

(10)

Note that $p_j$ can have values higher to 1 for $N_n \leq \sqrt{200}$, coyotes count per packet denotes 14. This mechanism enables the COA to diversify contacts among entire coyotes of population, that is, a artistic swap at world population. At species, packages generally contain two alphas; though COA assumes only one that is environmentally friendly. Consider reducing issue, alpha of $m^{th}$ pack on $t^{th}$ Time instant defined from

$$alpha_{n,m,t} = \{soc_{n,m,t} \in \text{arg}_n \{i \leq N_n \\text{ min } f(soc_{n,m,t})\}}$$

(11)

Owing to obvious mass intelligence sign at specification, COA considers coyotes to be properly organized. They share the social conditions as well as contribute to the maintenance of the packages. So, COA combines all information Calculating Coyotes and Cult of Culture

$$cul_{n,m,t} = \begin{cases} \frac{O_{m,i,i+1,t}}{2} & \text{if } N_n \text{ is odd} \\ \frac{O_{m,i,i+\frac{D}{2},t} + O_{m,i+\frac{D}{2},i+1,t}}{2} & \text{otherwise} \end{cases}$$

(12)

$O^{m,t}$ Stands for ranked social conditions coyotes of $m^{th}$ pack in $t^{th}$ every i in the [1, D] range at extra words; cultural trend the average for everyone in pack is calculated from social conditions Coyotes as particular set.

Considering the two main biological events in life, computes the age of birth as well as death, COA Coyotes (over a years), which $age\in N$. A novel coyote birth is written from composite social condition made up of two parents (selected at random) and environmental impact, such as

$$pup_{n,i} = \begin{cases} soc_{n,m,t} \text{rand}_i < P_s \text{ or } i = i_1 \\ soc_{n,m,t} \text{rand}_i \geq P_s + P_a \text{ or } i = i_2 \\ R_i & \text{Otherwise} \end{cases}$$

(13)
Here $r_1$ and $r_2$ denotes random coyotes as $m^{th}$ pack, $i_1$ and $i_2$ denotes two random dimensions of issue; $P_s$ scattering probability. $P_a$ denotes probability of association, R.J.A random number within decision variable $j^{th}$ dimension as well as $r_{nd}$ denotes random number $[0,1]$ Formed by uniform probability. Scattering as well as connecting the probability guides a cultural diversity for a coyote packet. COA early version, $P_s$ defined as

$$P_s = 1/D \quad (14)$$

$$P_s = 1 - P_a \quad (15)$$

$P_a$ establishes the same influence on parents.

Based on certain research, pubs have a 10% chance of dying previous to life, as well as older coyote, the higher probability of death. To keep the population level stable, the COA synchronizes the coyote’s birth as well as death explained at Alg. 1, here denotes $\omega$ and, correspondingly, coyote group is worse. It is more environmentally appropriate to puppy (i.e., group solutions that provide the cost of poor objective function) as well as coyotes count at group. Note that it is probable. Two or more coyotes are of equal age (fourth row). Although, the least adapted coyote dies.

To represent the cultural interactions within a package; COA considers, which coyotes are in alpha influence ($\delta_1$) as well as pack influence ($\delta_2$). At initial signifies a culture Differentiation as random coyote ($c_r_1$) alpha from Coyote package, second one refers to cultural diversity of random coyote ($c_r_2$) towards cultural trend of set. Random coyotes are selected using a uniform distribution the probability of $\delta_1, \delta_2$ are written as follow

$$\delta_1 = alpha^{m, j} - soc^{m, j}_{n_1} \quad (16)$$

$$\delta_2 = cult^{m, j} - soc^{m, j}_{n_2} \quad (17)$$

Therefore, the coyote is renewed using the new social status Alpha as well as pack influence by below equation

$$new\_soc^{m, j}_n = soc^{m, j}_n + r_1 \delta_1 + r_2 \delta_2 \quad (18)$$

$\delta_1$ And $\delta_2$ is an alpha weight as well as influence of package. At first, $\delta_1$ and $\delta_2$ are Random numbers defined within $[0, 1]$ range are uniformly generated probability. A novel social status is then assessed

$$new\_fit^{m, j}_n = f(new\_soc^{m, j}_n) \quad (19)$$

Coyote’s cognitive ability determines whether it is a new community Condition is better than old, which means

$$soc^{m, j}_n = \begin{cases} new\_soc^{m, j}_n & new\_fit^{m, j}_n < fit^{m, j}_n \\ soc^{m, j}_n & Otherwise \end{cases} \quad (20)$$

At last, coyote social status is better adapted selectively applied with surroundings as well as employed worldwide solution of issue. COA pseudo-code is explained at Alg. 2, here $N_n$ may be place from initial guess range $[5,10]$ and $N_m$ may then be tuned as total population size of the algorithm is defined.

### Algorithm 1: Birth and death inside a pack.

1: Calculate $\omega$ and $\phi$.
2: if $\phi = 1$ then
3: Pup survives and only coyote on $\omega$ dies.
4: else if $\phi > 1$ then
5: Pup survives and earliest coyote on $\omega$ dies.
6: else
7: Pup dies.
8: end if

### Figure 1: Algorithm of birth and death within a packet.

#### Algorithm 2: Pseudo code of COA

1: Start $N_m$ packs with $N_n$ coyotes every (Eqn. 2).
2: Check coyote’s adaptation (Eqn. 3).
3: when stopping criterion is not achieved do
4: for every m pack do
5: Define alpha coyote of package (Eqn. 5).
6: Calculate social tendency of package (Eqn. 6).
7: for every n coyotes of m pack do
8: Upgrade social condition (Eqn. 12).
9: Estimate novel social condition (Eqn. 13).
10: Adaptation (Eqn. 14).
11: end for
12: Birth and death (Eqn.7 and Alg. 1).
13: end for
14: Transition among package (Eq. 4).
15: Upgrade coyotes’ ages.
16: end while
17: Choose better adapted coyote.

### Figure 2: Pseudo code of the COA
4. RESULT

The benchmark functions from CEC2015 are used as a dataset in the proposed method. The dataset has different classification dimensions and the benchmark from the IEEE CEC 2015 has the dimensions as 30, 50, and 100. 40 benchmark functions have set for the comparisons of existing with the proposed method. The result of these multi-level image thresholding using Coyote Optimization
values from COA. COA has 7-9 ranking value. In these algorithms MRPF has less ranking value ranging as 1.5-3.4.

An above figure shows that mean as well as standard deviation of large level threshold. The mean level of the COA was higher than the others. In this high level thresholding, the ranking of COA was from 8.9 to 7.9. Here also MFPA has the lesser ranking values ranged as 0.5 to 2.3. PSO has the ranking range as 7.9 to 5.9 it is the second highest ranking value. Remaining all are has the lesser ranking value from the COA.

![COA](image)

**Figure 7:** Average ranking of Coyote Optimization Process

The above figure explains the average ranking of Coyote Optimization process. It is used to evaluate robustness of estimating the potential. For hybrid operations, for example, COA is very small the average ranking is not even reached First place (40% versus 45% of ABC). It will happen because it still exists when the COA does not reach the top reached good ratings and has generally performed awarded outcomes to another method. At fact, COA has received an excellent average rating at major cases; detachable and does not provide better outcomes.

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**Table 1:** Numerical ranking of the coyote optimization process

The above table represents the numerical ranking of the coyote optimization process. Here two levels of ranking are explained as, normal level and high level. However, COA has the normal value as 8.875 and high level value as 9. The PSO value has the value as 8 for both normal and high level ranking. All of others have lower than the COA.

![Graph](image)

**Figure 8:** Comparisons of Average minimum cost and number of functions evaluation

The figure 8 shows the comparisons between the average minimum cost and number of function evaluation by existing techniques and outcomes shows that proposed technique denotes best cost.

![Graph](image)

**Figure 9:** Convergence performance

The figure 9 shows that the convergence performance, the premature convergence avoids the dedicating pollination of global strategy in the success of convergence. The
optimal threshold is compared with the existing method and the proposed method, the efficiency is searched in the modified strategy is the advantage of the proposed method. The proposed algorithm is offering very clear convergence performance on normal levels of the threshold as well as getting the best performance on COA threshold.

Figure 10: Accuracy

Figure 10 shows that the accuracy of the thresholding methods. The accuracy is better in the proposed method while comparing with other existing methods. The accuracy is the degree of closeness in a measured value to the actual value.

Figure 11: Precision

Figure 11 shows the comparison of precision for various methods to the proposed method. The precision estimates the samples in different sample with the standard error. It is the description of the random errors and a measure of variability of statistical.

The execution time is compared with the existing methods in the figure 12. The time spent for the execution of the system that includes the time that spent for the runtime of the execution.

5. CONCLUSION

This study presents a new metaheuristic algorithm that uses Coyote Optimization (COA) based on bio-inspired mechanism that decides more than one threshold of provided image as well as segments the image in some brightness regions that equivalent with background as well as various objects. COA mainly has two parameters, packets count as well as coyotes per packet count that describes the image segmentation. COA has been used to determine and segmenting the multi-level images into sub-regions and it separate the object image from the background image. COA in multi-level thresholding has outperformed the less computational expensive and that gives the accurate threshold value for image segmentation. And they obtained outcomes display the proposed technique (COA) may create extra powerful solutions and accuracy than other methods when there are technical criteria are still satisfied.

REFERENCES


