A Discrete Harris Hawk Algorithm For Detecting Parkinson's: A Progressive Neurodegenerative Disorder

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Abstract

A discrete harris hawk optimization (DHHO) algorithm which integrates effectiveness of levy flights and an excellent classifier, support vector machine (SVM), has been proposed for selecting features from the Parkinson's dataset for predicting Parkinson's disease. Harris hawk algorithm (HHO) mimics the pray foraging mechanisms of harris hawks in nature. In the proposed algorithm, discrete harris hawk optimization (DHHO) is used as a feature selection tool, which targets to reduce the noise in features of the parkinson's datasets to improve the SVM classifier's prediction accuracy. Although HHO can obtain optimal solutions for specific problems, it stagnates in local optima. A new levy flight strategy is integrated to enhance the exploitation capability of HHO to jump out the local optima. Results from experiments conducted on Parkinson's datasets demonstrated that the proposed algorithm can provide a more reliable solution than other well-known algorithms.

Keywords: Harris Hawk, Swarm Intelligence, Levy Flight, Parkinson's, Discrete Algorithm

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1. Introduction

In recent decades, swarm intelligence algorithms (SIAs) have attracted the researchers because of their low computing cost, simplicity, flexibility, and gradient-free mechanisms [1]. The research in swarm intelligence algorithms (SIAs) has increased significantly in recent decades. SIAs try to generate effective and optimal solutions by removing not useful solutions with the help of a fitness function. Some of the SIAs proposed and applied to combinatorial problems are bacteria foraging optimization (BFO) [2], cuckoo search (CS) [3], bat algorithm (BA) [4], firefly algorithm (FA) [5], artificial bee colony (ABC) [6], shuffle frog leaping algorithm (SFLA) [7], particle swarm optimization (PSO) [8], ant colony optimization (ACO) [9], chicken swarm optimization (CSO) [10], gray wolf optimizer (GWO) [11], salp swarm algorithm (SSA) [12], naked mole-rat algorithm (NMRA) [13], social spider optimization (SSO) [14], moth flame optimization (MFO) [15], whale optimization algorithm (WOA) [16], dragonfly algorithm (DFO) [17], water wave optimization (WWO) [18], spider monkey optimizer (SMO) [19], sparrow search algorithm (SSA) [20], fruit fly algorithm (FFA) [21], pigeon inspired algorithm (PIA) [22], deer hunting optimization (DHO) [23], earthworm optimization (EWO) [24], squirrel search optimization (SSA) [25], tree seed algorithm (TSA) [26], and butterfly optimization algorithm (BOA) [27]. In this paper, we propose a discrete version of harris hawk algorithm (HHO) for selecting features from the parkinson's dataset to help SVM in classification tasks. HHO is a recently

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proposed metaheuristic algorithm in 2019 [28]. Generally, HHO mimics the concepts of harris hawks to explore the prey, surprise pounce, and different attack strategies of hawks in nature. According to the literature, HHO showed superior performance for several benchmark tests compared to other well-established metaheuristic algorithms [28-29]. Among the competitors, HHO is highly capable of maintaining a well stable balance between exploration and exploitation, which allows it to score the best properties in optimization tasks. HHO utilizes a series of search strategies in exploitation that enables it to provide a constructive impact on local search. Thus, HHO can be considered as a powerful algorithm for optimization problems.In the field of SIAs, the no free lunch theorem [30] says that there is no single solution to all optimization problems. Therefore, numerous authors developed their interest in improving the algorithms available in the literature as well as developing new algorithms. This motivates us to propose a new discrete version of HHO in this work.

In particular, this paper made the following main contributions:

1. The HHO algorithm has been modified and applied for diagnosing the Parkinson's disease.
2. The proposed algorithm is able to diagnose the occurrence of Parkinson's disease at early stages and hence increases the chances of a suitable cure.
3. The proposed algorithm reduces the required set of features for the diagnosis of the Parkinson's disease.
4. Higher accuracy of SVM classifier has been achieved using the dataset with reduced attributes.

The rest of this document is organized as follows. Related work is given in section 2. A brief introduction of HHO is given in Section 3. Section 4 describes the proposed discrete HHO. The results and discussion of the proposed algorithm are given in Section 5, which mainly applies to Parkinson's datasets. Section 6 contains the conclusions and prospects.

2. Related Work

Feature selection is playing a significant role in any classification task. Generally, feature selection can be categorized into two classes: filter and wrapper. The filter method is simple, and it can obtain the results faster. However, the filter method does not dependent on the learning algorithm, thus resulting in unsatisfactory performance [31-32]. As compared to the filter method, the wrapper method can usually provide higher classification accuracy. The wrapper method includes a machine learning algorithms part of the evaluation, which enables it to achieve better classification results than the filter method. Thus, wrapper methods have more widely used in feature selection works [33–35].

Swarm intelligence algorithms (SIAs) are suggested and proved a valuable performance for feature selection tasks. We present a review of the some research done very recently using SIAs for selecting features from the Parkinson's dataset.

Zhennao Cai et.al. presented an improved fuzzy k-nearest neighbour (FKNN) method for the early detection of Parkinson's disease based upon vocal measurements in 2018 [36]. It was an evolutionary approach named CBFO-FKNN developed by coupling the chaotic bacterial foraging optimization with gauss mutation (CBFO) approach with FKNN. The integration of the CBFO technique efficiently resolved the parameter tuning issues of the FKNN. Sharma et. al. presented a modified grey wolf optimizer (MGWO) grounded on the traditional grey wolf optimizer (GWO), which acts as a search strategy for feature selection in 2018 [37]. MGWO used random forest, k-nearest neighbour and decision tree classifiers for prediction purpose on selected features. Gupta et. al. presented an improved and optimized version of crow search algorithm (OCSA) for predicting the Parkinson's disease in 2018 [38]. The algorithm produced an accuracy of 100% and help individual to have proper treatment at early stage. The performance of OCSA has been compared with the original chaotic crow search algorithm (CCSA) and found competitive. Sharma et. al. presented a binary ant-lion optimisation (ALO) algorithm for diagnosing patients for Parkinson's disease at early stages in 2019 [39]. The proposed modified version of ALO selects the optimal features from the two different Parkinson's datasets and achieved accuracy of 95.91%. Dash et. al. presented a novel chaos-based stochastic model by combining the characteristics of chaotic firefly algorithm with kernel based naive bayes (KNB) algorithm for diagnosis of Parkinson's disease at an early stage in 2019 [40]. The efficiency of the model is tested on a voice measurement dataset that is collected from UCI repository. The diversification and intensification capability of chaos-based firefly algorithm is enhanced by introducing six types of chaotic maps. Ozturk et. al.

presented a two stage whale optimization method for the efficient classification of data from Parkinson's disease and normal individuals is proposed in 2020 [41]. This algorithm used dimensionality techniques such as PCA, ICA, Relieff, and RICA. Sehgal et. al presented a novel modified grasshopper optimization algorithm for selecting the features from the Parkinson's dataset in 2020 [42]. Popular classification algorithms like random forest, decision tree and k-nearest neighbour classifier were used in evaluation on selected features from the Parkinson's dataset. Olivares et. al. proposed an optimized extreme learning machine by using the BAT Algorithm, which boosts the training phase of the machine learning to increase the accuracy, and decreasing or keeping the loss in the learning phase in 2020 [43]. This method was developed to predict the Parkinson's disease form the audio dataset taken from UCI machine learning repository. Haolun Li presented a hybrid feature selection algorithm based on an improved discrete artificial bee colony algorithm to improve the efficiency of feature election in 2021 [44]. The algorithm combines the advantages of filters and wrappers to eliminate most of the not useful features and provides the optimal subset of features. Nadimi-Shahraki et. al presented a binary moth-flame optimization (B-MFO) is proposed to select effective features from small and large medical datasets in 2021 [45]. Three categories of B-MFO were developed using S-shaped, V-shaped, and U-shaped transfer functions to convert the canonical MFO from continuous to binary version. The results attained were statistically analysed using the Friedman test and proved best the algorithms compared. Koyunku presented a Parkinson's disease recognition method using gauss map based chaotic particle swarm–neural network [46]. He performed the classification of two well-known Parkinson's datasets including the features attained by recordings. SM-CPSO, DWPSO and CDW-PSO are used to compare the results achieved with Gauss map based CPSO (GMCPSO) on classification of PD.

3. Material and Methods

3.1 Basic Harris Hawk algorithm

Harris hawk algorithm (HHO) is a swarm-based algorithm introduced by Heidari et. al. in 2019 [28]. Harris hawk algorithm imitates the foraging behaviour of the harris hawks. The strategies employed for exploring pray, attacks and surprise pounce are mimicked in this algorithm. In this algorithm, hawks represent candidate solutions and pray represent itself as the final optimal solution. The harris hawk uses its powerful eyes to track and do surprise attacks to catch the prey detected.

In this optimizer, the search agents are updated using two phases of exploration and four phases of exploitation. It utilizes several time-varying mechanisms with a greedy scheme to enhance the quality of results [28-29]. The symbols used here are described in table 1.

Table 1. The symbols used in mathematical modeling of HHO

Description	Symbol
Position vector of hawks, location of nth hawk	X, Xn
Position of rabbit (best agent)	X_r
Position of a random hawk	X_k
Mean position of hawks	X_m
Swarm size, iteration counter, maximum iterations	*N, t, T*
Random numbers in [0,1]	$r_1, r_2, r_3, r_4, r_5, q$
Dimension, upper and lower bounds of variables	*ub, lb*
Escaping energy, Initial state of energy	E, E_0
Random numbers in [0,1]	*u,v, rand*
Jump strength	*J*
Difference between prey position and current hawk	ΔX
Random vector	α
S-shaped & *V*-shaped Transfer function	*T(X)*
Dimension	*d*
Complement of *X*	$\neg X$

3.1. Exploration Phase

Harris hawk algorithm performs exploration phase in two phases which are computed as follow [28-29]:

$$X(t+1) = \begin{cases} X_k(t) - r_1|X_k(t) - 2r_2X(t)| & q \geq 0.5 \\ (X_r(t) - X_m(t) - r_3(lb + r_4\,(ub - lb)) & q < 0.5 \end{cases} \tag{1}$$

$$X_m(t) = \frac{1}{N}\sum_{n=1}^{N} X_n(t) \tag{2}$$

3.2. Transition from Exploitation to Exploration Phase

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{3}$$

$$E_0 = 2r - 1 \tag{4}$$

Here E and E_0 represents escaping energy and the initial state of energy

3.2. Exploitation Phase

3.2.1. Soft Besiege

The soft besiege happens with following equations [28-29].

$$(t+1) = \Delta X(t) - E|JX_r(t) - X(t)| \quad (5)$$

$$\Delta X(t) = (X_r(t) - X(t) \quad (6)$$

$$J = 2(1 - r_5) \quad (7)$$

3.2.2. Hard Besiege

The HHO performs the hard besiege using following equation [28-29]:

$$X(t+1) = X_r(t) - E|\Delta X(t)| \quad (8)$$

3.2.3. Soft Besiege with Progressive Rapid Dives

This phase is occurred when $r < 0.5$ and $|E| \geq 0.5$. The hawk progressively selects the best possible dive for the new position based on equations 9 [28-29]:

$$Y = X_r(t) - E|JX_r(t) - X(t)| \quad (9)$$

$$Z = Y + \alpha \times levy(D) \quad (10)$$

Also, a Levy based pattern is used to model this phase which is based on equation 10. Levy indicates a Levy function here which is calculated using equation 11 and 12 [28-29]:

$$Levy(x) = 0.01 \times \frac{\mu \times \sigma}{|v|^{1/\beta}} \quad (11)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (12)$$

Here, β is a default constant set to 1.5. In this phase, the position of the hawk is updated as in Equation (13). The Y and Z are calculated using equations 9 and 10.

$$X(t+1) = \begin{cases} Y & if\ F(Y) < F(X(t)) \\ Z & if\ F(Z) < F(X(t)) \end{cases} \quad (13)$$

3.2.4. Hard Besiege with Progressive Rapid Dives

The last situation is hard besieged with progressive rapid dives, in which we have following situation.

$$X(t+1) = \begin{cases} Y & if\ F(Y) < F(X(t)) \\ Z & if\ F(Z) < F(X(t)) \end{cases} \quad (14)$$

Where, Y, Z, and $X_m(t)$ are calculated using equations 15, 16 and 2 respectively [28-29]:

$$Y = X_r(t) - E|JX_r(t) - X_m(t)| \quad (15)$$

$$Z = Y + \alpha \times levy(D) \quad (16)$$

4. Proposed Discrete Harris Hawk Algorithm

Feature selection is considered as a discrete optimization problem that represents the solutions on the discrete (binary) search space. However, HHO is designed to solve the continuous optimization problems, which is not suitable for the feature selection problem. To develop the discrete version of HHO, the solutions should be representing in binary form (either 0 or 1). Thus, several modifications are needed to meet the requirement. In this algorithm, we have used transfer functions [47-48] to convert an original HHO into a discrete one.

The pseudocode of the basic HHO is given below.

Begin:
Inputs: *N and T*
Output: *Xr , Initialize Xi(i = 1; 2; : : : ;N)*
While (stopping condition is not met)
Calculate the fitness values
Set Xr as the best solution
for (each hawk (Xi))
Update E0 and jump strength J .
Update E by Eq. (3)
Update E0 and jump strength J .
Update E by Eq. (3)
if *(|E| ≥ 1)* ***then***
Update the location vector by Eq. (1)
if *(|E| < 1)*
if *(r ≥0.5 and |E| ≥ 0.5)*
Update the location vector by Eq. (4)
else if *(r ≥0.5 and |E| < 0:5)*
Update the location vector by Eq. (6)
else if *(r <0.5 and |E| ≥ 0.5*
Update the location vector by Eq. (10)
else if *(r <0.5 and |E| < 0:5) Update the location vector by Eq.* (11)
Return Xr
End

Figure 1. The Pseudocode of the basic HHO Algorithm

4.1 Transformation of Solutions

According to literature, the utilization of transfer function is one of the effective ways to convert continuous optimizer into a discrete one [47-48]. In this study, we use four S-shaped ($S1$–$S4$) and V-shaped ($V1$–$V4$) transfer functions to change the continuous HHO into the discrete version. By integrating the transfer function into discrete HHO, the algorithm is able to perform the search on the discrete search space. In DHHO, the position of the hawk is updated in following two stages [49]. Symbols used here are described in table 1.

$$X_i^d(t+1) = \begin{cases} 1, & if\ rand(0,1) < \Delta X_i^d(t+1) \\ 0, & Otherwise \end{cases} \quad (17)$$

$$X_i^d(t+1) = \begin{cases} \neg X_i^d(t), & if\ rand(0,1) < T(\Delta X_i^d(t+1)) \\ X_i^d(t), & Otherwise \end{cases} \quad (18)$$

5. Results And Discussion

5.1. Datasets

The proposed approach evaluated using two datasets that are given below.

Dataset 1: This dataset known as Speech PD and available in the UCI [51]. The speech PD dataset consists of voice data of 31 individuals. Out of 31 individuals, 23 individuals were detected with Parkinson's. This dataset have 195 voice instances of 48 healthy and 147 patients in the age range between 46 to 85 years. It stores on an average six phonations of the vowel letters ("a" & "o"). The length of each phonation is 36 seconds. Table 2 describes the features of this Speech PD dataset.

Dataset 2: This dataset is collected from UCI Repository [52]. The data were gathered from 188 patients with Parkinson's disease (107 men and 81 women) with ages ranging from 33 to 87 at the department of neurology in faculty of medicine, Istanbul University. The control group consists of 23 men and 41 women with ages varying between 41 and 82. The microphone is set to 44.1 KHz and the sustained phonation of the vowel "a" was collected from each subject with three repetitions.

5.2 Evaluation Measures

Different metrics such as specificity, sensitivity, accuracy, precision and F-Measure given by Karalolis et al. in 2010 [53] are used for the evaluation. They use the following defined rules.

- **True Positive (TP):** The number of Heart Disease Patients classified correctly.
- **True Negative (TN):** The Number of patients not having heart disease correctly classified.
- **False Positive (FP):** The Number of healthy patients wrongly classified as heart disease patient.
- **False Negative (FN):** The number of healthy patients classified as heart disease patients.

We can define all measures as per the rules given above. Accuracy shows how the algorithm performs altogether. Accuracy is computed as a ratio of the correct predictions to total predictions. It is computed using equation 19.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \times 100\% \quad (19)$$

Sensitivity measures the number of actual instances rightly predicted. It is computed using equation 20.

$$Sensitivity = \frac{TP}{TP+FN} * 100\% \quad (20)$$

Specificity measures number of unreal instances rightly predicted. It is computed using equation 21.

Table 2. The Description of the features of Speech PD dataset1 [51]

Features	**Description**
MDVP:Fo(Hz)	Average vocal fundamental frequency
MDVP:Fhi(Hz)	Maximum vocal fundamental frequency
MDVP:Flo(Hz)	Minimum vocal fundamental frequency
MDVP: Jitter (%)	Several measures of variation in
MDVP:Jitter(Abs)	fundamental frequency
MDVP:Shimmer	Several amplitude variations measures
NHR	Two measures of ratio of noise to tonal
HNR	components in the voice
RPDE	Two nonlinear dynamical complexity
DFA	Signal fractal scaling exponent
Spread1	Three nonlinear measures of fundamental
Spread2	Frequency variation
MDVP:RAP	---
MDVP:PPQ	---
Jitter:DDP	----
Shimmer:APQ3	--
Shimmer:APQ5	---
MDVP:APQ	---
Shimmer:DDA	---
MDVP:Shimer(dB)	---
PPE	---
MDVP:RAP	--
Class Label	(1) Parkinson's (2) healthy

$$Specificity = \frac{TN}{TN+FP} * 100\% \quad (21)$$

The proportion of the rightly predicted actual instances is known as precision and computed using equation 22.

$$Precision = \frac{TP}{TP+FP} * 100\% \quad (22)$$

The accuracy is not a good measure when the number of false instances is increased. Other measures like G-mean and F-measure proposed by Kubat and Matwin [54], and Lewis and Gale [55], respectively, are used to evaluate the algorithm's performance. G-mean and F-measure are computed using Equations 23 and 24.

$$G - mean = \sqrt{Sensitivity * Specificity} \tag{23}$$

$$F - measure = \frac{(\beta 2 + 1) * Precision * Sensitivity}{\beta 2 * Precision + Sensitivity} \tag{24}$$

Table 3. The Results obtained for Speech PD dataset1

Algorithm	Acc (%)	Sens (%)	Spec (%)	Prec (%)	GM (%)	FM (%)
CBFO-KNN	96.3	97.2	96.6	96.8	96.9	97.0
MGWO	92.8	95.2	93.5	93.8	94.3	94.5
OCSA	95.7	96.7	96.3	96.1	96.5	96.4
ALO	97.2	98.1	96.4	98.3	97.3	98.2
DHHO	99.4	99.0	98.3	99.9	98.6	99.4
CFFA	78.0	80.3	80.2	80.5	80.3	80.4
WOA	95.9	95.1	96.2	96.7	95.6	95.9
MGHOA	82.7	83.5	84.6	85.2	84.1	84.3
BAT	91.5	92.3	91.9	92.8	92.1	92.6
DABC	96.6	97.2	98.2	97.6	97.7	97.4
BMFO	88.5	89.4	89.7	90.2	89.6	89.8
GMCPSO	83.2	84.6	84.9	85.5	84.8	85.1

Table 4. The Results obtained for Speech PD dataset 2

Algorithm	Acc (%)	Sens (%)	Spec (%)	Prec (%)	GM (%)	FM (%)
CBFO-KNN	96.7	97.5	96.8	96.8	97.2	97.2
MGWO	91.9	94.3	94.1	94.9	94.2	94.6
OCSA	96.1	97.2	97.5	97.1	97.4	97.1
ALO	97.7	98.2	96.9	98.1	97.5	98.1
DHHO	99.3	99.1	98.8	99.5	98.9	99.3
CFFA	80.5	81.5	82.3	82.3	81.9	81.9
WOA	94.9	95.8	96.7	96.4	96.3	96.1
MGHOA	81.9	82.9	83.2	84.8	83.1	83.9
BAT	92.6	93.1	92.8	93.7	92.9	93.4
DABC	97.1	97.1	97.9	97.9	97.5	97.5
BMFO	89.2	90.5	90.8	91.3	90.6	90.9
GMCPSO	84.1	85.2	85.8	86.7	85.5	85.9

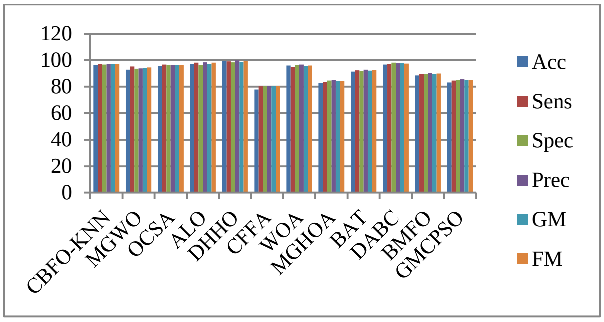

Figure 2. Comparision of the Results obtained for Speech PD dataset1

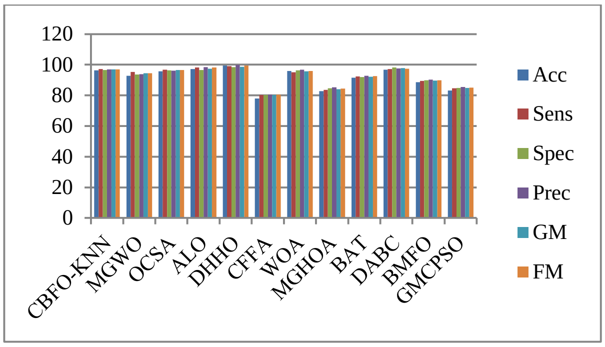

Figure 3. Comparision of the Results obtained for Speech PD dataset1

5.3. Discussion

The results obtained with the both datasets are detailed in table 3 and table4. Both the tables also contain the results obtained with the algorithms used for comparision. Figures 2 and 3 depicts the comparision graphically. In this paper, 2 Parkinson's datasets were downloaded from UCI, and Kaggle data repositories to evaluate the proposed DHHO algorithm. Table 1 lists these datasets along with their number of features, instances and classes. All the datasets are characterized by balanced distribution of their classes. To validate the proposed algorithm, three well known SIAs were used for comparison purposes: CBFO-KNN [36], MGWO [37], OCSA [38], ALO [39], CFFA [40], WOA [41], MGHOA [42], BAT [43], DABC [44], BMFO[45], and GMCPSO [46]. All the experiments were executed on a personal machine with Intel inside i3 processor and memory of 4 GB running Windows10 64 bit operating system. The optimization algorithms are all implemented in Python. The maximum number of iterations and the population size were set to 50 and 100 respectively. In this work, the SVM classifier is used to evaluate individuals in the DHHO algorithm. The used evaluation measures are accuracy, sensitivity, specificity, precision, G-mean and F-measure. Inspecting the results in Table 3 and 4, it seems clearly that the proposed algorithm surpasses all algorithms with significant difference. This is due to the four phases of exploitation and use of levy flights

6. Conclusion

Harris hawks algorithm is a new swarm-based algorithm inspired by the pray foraging process of harris hawks. It has mainly two phases, exploration and exploitation. Exploration phase consists of two phase while four phases are devoted to exploitation. In this paper, we developed a new discrete HHO for the first time. We used it for selecting features from the Parkinson's datasets. In addition, when we use these datasets, we have a large feature space that makes the FS process much harder. The purpose of this paper was to compare the efficacy in term of different well-known metrics with CBFO-KNN, MGWO, OCSA, ALO, CFFA, WOA, MGHOA, BAT, DABC, BMFO, and GMCPSO methods. The results and analysis show the advantages of discrete HHO with *S & V* shaped transfer functions in terms of exploration and exploitation inclinations. The results suggest that the proposed DHHO can be utilized as a favorable algorithm in dealing with small as well as high dimensional real-world datasets. HHO is still new and there are several new directions to extend the operations of HHO for tackling more real-world datasets. One of the potential directions is to apply HHO to hybrid wrapper-filter methods. In future, we are going to explore this direction by developing new enhanced variants of discrete HHO.

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