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# Spider Monkey Optimization Algorithm: Estimation of Frequency-Modulated (FM) Sound Waves

Vaibhav Hiranandani[1], Sneha Sharma[2], Ajay Saini[3]
[1-2]UG Scholar, [3]Assistant Professor, Department of CSE, Poornima Institute of Engineering & Technology, Jaipur, India

***Abstract:* Spider Monkey Optimization (SMO) algorithm is most recent swarm intelligence based nature inspired algorithm which mimics the intelligent behavior of spider monkeys while searching for food. Frequency-Modulated (FM) sound wave synthesis has an imperative function in more than a few contemporary music systems and to optimize the parameter of an FM synthesizer is an optimization problem with six dimensions. However, it is found that the SMO algorithm is good in comparison to other competitive population based algorithm. Therefore, in this paper a self adaptive Spider Monkey optimization (SMO) algorithm is presented to solve parameter estimation for frequency-modulated sound wave. The proposed strategy is self-adaptive in nature and therefore no manual parameter setting is required. The proposed technique is named as an Adaptive Spider Monkey optimization (ASMO) algorithm. ASMO gives better results for parameter estimation for frequency-modulated sound wave in comparison to other considered algorithms like basic SMO, ABC and DE.***

***Keywords:* Spider Monkey Optimization Algorithm, Swarm Intelligence, Engineering Optimization Problems, Nature Inspired Algorithms.**

## I. INTRODUCTION

Spider Monkey Optimization (SMO) algorithm was introduced by J. C. Bansal *et al.* [1] in year 2013. It is a recent popular swarm intelligence based algorithm. This algorithm is stimulated by means of the extra ordinary behavior of Spider Monkeys while searching for food. This algorithm based on fission-fusion social structure (FFSS). It falls into category of Nature Inspired Algorithms (NIA) that is inspired by some natural phenomenon or extraordinary behavior of intelligent insects. NIAs include Evolutionary algorithms, Immune algorithms, neural algorithm, Physical algorithms, Probabilistic algorithms, stochastic algorithms and Swarm algorithms based on their source of inspiration. Resembling other population based optimization algorithm, SMO consists of a population of possible solutions. Here possible solutions are represented by food sources of spider monkeys. The superiority of a food source is decided by calculating its fitness. The SMO algorithm is comparatively an easy, rapid and population based stochastic search strategy. While searching for optimal solution this algorithm need to maintain balance between two basic activities named the assortment process, which make sure the exploitation of the preceding knowledge and the adaptation process, which empowers exploring diverse fields of the search space. However, it has been observed that SMO algorithm is very good in exploration of local search reason and exploitation of best feasible solutions in its immediacy [2] [3]. Therefore, to solve a complex problem like parameter estimation for frequency-modulated sound wave this paper uses a new variant of SMO algorithm. The proposed algorithm is adaptive in nature as it automatically adjusts the search radius while local leader phase and local leader decision phase during position update along with fitness based position update.

Recently S. Kumar *et al.* proposed two variants of SMO algorithm. First is Modified Position Update in Spider Monkey Optimization Algorithm [3]. This algorithm modifies together local leader phase and global leader phase using customized golden section search (GSS) [4] technique stimulated by memetic search in ABC [5]. Memetic strategy inspired by GSS strategy recently used in various algorithms like RMABC [6], IMeABC [7], EnABC [8], MSDE [9], IoABC [10]. Second is Fitness Based Position Update on Spider Monkey Optimization Algorithm (FPSMO) [2]. FPSMO update position based on the individual's fitness. It assumes that best fitted solution has good neighbors and modifies the step size according to its fitness. It takes a large step for high fitted solution and a small step for low fitted solutions.

Rest of the paper is prepared as follows: Major steps of SMO algorithm are explained in section II. Section III describes parameter estimation for frequency-modulated sound wave problem in detail. In section IV, newly anticipated variant of SMO expla00ined. The solution of parameter estimation for frequency-modulated sound wave and performance of the proposed strategy is analyzed in section V. At last, in section VI, paper is concluded followed by references.

## II. SPIDER MONKEY OPTIMIZATION ALGORITHM

Extraordinary food foraging conduct of spider monkeys motivated J. C. Bansal et al. [1] to develop a new population based meta heuristics. They named it Spider Monkey Optimization algorithm. The original SMO algorithm given by J. C. Bansal et al. [1] consists of seven phases.

- Population Initialization
- Local Leader Phase (LLP)
- Global Leader Phase (GLP)
- Global Leader Learning (GLL) Phase

- Local Leader Learning (LLL) Phase
- Local Leader Decision (LLD) Phase
- Global Leader Decision (GLD) Phase

*A. Phases of Spider Monkey Optimization (SMO) Algorithm:*

SMO algorithm is a population based iterative approach. It has seven key steps. The complete depiction of every phase is summarized in next few subsections.

*1) Population Initialization:*

At first, a population of $N$ spider monkeys initialized. Initial population denoted by a $D$-dimensional vector $SMO_i$, where $i = 1, 2, ..., N$. Every spider monkey $SMO$ represents a feasible solution for the consideration problem. Every $SMO_i$ is initialized using Eq. (1).

$$SMO_{ij} = SMO_{\min j} + \phi \times (SMO_{\max j} - SMO_{\min j}) \quad where\ \phi \in (0,1) \tag{1}$$

*Here* $SMO_{min\ j}$ and $SMO_{max\ j}$ indicate lower and upper bounds of $SMO_i$ in $j^{th}$ direction correspondingly.

*2) Local Leader Phase (LLP):*

The subsequent phase is Local Leader Phase. Based on the experience of local leader and group members SMO modernize its present location. It compares fitness new location and current location and applies greedy selection. The ith SMO that also belongs to $k^{th}$ local group update its location using Eq. (2).

$$SMO_{newij} = SMO_{ij} + rand[0,1] \times (LL_{kj} - SMO_{ij}) + rand[-1,1] \times (SMO_{rj} - SMO_{ij}) \tag{2}$$

Where $SMO_{ij}$ denote $i^{th}$ SMO in $j^{th}$ dimension, $LL_{kj}$ correspond to the $k^{th}$ local group leader location in $j^{th}$ dimension. $SMO_{rj}$ is the $r^{th}$ SMO which is arbitrarily selected from $k^{th}$ group such that $r \neq i$ in $j^{th}$ dimension.

*3) Global Leader Phase (GLP):*

The Global Leader phase (GLP) starts just after finishing the LLP. Based on experience of Global Leader and members of local group SMO modernize their position using Eq. (3).

$$SMO_{newij} = SMO_{ij} + rand[0,1] \times (GL_j - SMO_{ij}) + rand[-1,1] \times (SMO_{rj} - SMO_{ij}) \tag{3}$$

Where $GL_j$ stands for the global leader's position in $j^{th}$ dimension and $j \in \{1, 2, ..., D\}$ denotes a randomly selected index.

The $SMO_i$ updates their locations with the help of probabilities $p_i$'s.Probability of a particular solution calculated using its fitness.There are number of different methods for computing fitness and probability, here $p_i$ computed using Eq (4).

$$p_i = 0.9 \times \frac{fitness_i}{fitness_{\max}} + 0.1 \tag{4}$$

*4) Global Leader Learning (GLL) Phase:*

Now global leader modify its location with the help of some greedy approaches. Highly fitted solution in current swarm chosen as global leader. It also perform a check that the position of global leader is modernize or not and modify Global Limit Count accordingly.

*5) Local Leader Learning (LLL) Phase:*

Now local leader modify its location with the help of some greedy approaches. Highly fitted solution in current swarm within a group chosen as local leader. It also perform a check that the position of local leader is modernize or not and modify Local Limit Count accordingly.

*6) Local Leader Decision (LLD) Phase:*

In this phase decision taken about position of Local Leader, if it is not modernized up to a threshold a.k.a. Local Leader Limit ($LL_{limit}$). In case of no change it randomly initializes position of LL. Position of LL may be decided with the help of Eq. (5).

$$SMO_{newij} = SMO_{ij} + rand[0,1] \times (GL_j - SM_{ij}) + rand[0,1] \times (SM_{ij} - LL_{kj}) \tag{5}$$

*7) Global Leader Decision (GLD) Phase:*

In this phase decision taken about position of Global Leader, if it is not modernized up to a threshold a.k.a. Global Leader Limit ($GL_{limit}$), and then she creates subgroups of small size. Number of subgroups has upper bound named as maximum number of groups (MG). During this phase, local leaders are decided for newly created subgroups using LLL process.

The SMO algorithm has four control parameters named Local leader limit, Global leader limit, maximum number of group and perturbation rate. If we have swarm of size $N$ then maximum number of groups should be $N/10$. Local leader limit should be $D*N$, with dimension-$D$. Global leader limit should be in range [$N/2$, $2N$] and perturbation rate should be in range [0.1, 0.9].

## III. PARAMETER ESTIMATION FOR FREQUENCY MODULATED SOUND WAVES PROBLEM

However computers have been applied to synthesize sound with a variety of synthesize methods. It is still required to fine-tune the parameters of the synthesizers by hearing and unique sounds. For a large amount of people, regulating parameters is a mind-numbing job, and experiences are also desired because of the intricacy of the synthesis structure, especially for FM (Frequency Modulation) synthesis after introduction of

FM synthesis, is a simple and commanding process for creating and controlling intricate spectra in classical sound synthesis. In contrast to classical approaches of trial and error, evolutionary algorithms have been used in finding parameters of FM synthesizers. GA (Genetic Algorithm), in particular, is the most successful algorithm dealing with complex solution space.

Frequency-Modulated (FM) sound wave amalgamation has a significant role in more than a few contemporary music systems. The parameter optimization of an FM synthesizer is an optimization problem with six dimension where the vector to be optimized is $X = \{a_1, w_1, a_2, w_2, a_3, w_3\}$ of the sound wave given in equation (6). The problem is to produce a sound (6) analogous to target (7). This problem is a exceedingly intricate multimodal one having strong epistasis, with minimum value $f(X) = 0$. The expressions for the anticipated sound and the target sound waves are specified as:

$$y(t) = a_1.\sin(\omega_1.t.\theta + a_2.\sin(\omega_2.t.\theta + a_3.\sin(\omega_3.t.\theta)))$$

$$y_0(t) = (1.0).\sin((5.0.t.\theta - (1.5).\sin((4.8).t.\theta + (2.0).\sin((4.9).t.\theta)))$$

Respectively where $\theta = 2\pi/100$ and the parameters are defined in the range [-6.4, 6.35]. The fitness function is the summation of square errors between the estimated wave (6) and the target wave (7) as follows:

$$f_{11}(x) = \sum_{i=0}^{100} (y(t) - y_0(t))^2$$

Acceptable error for this problem is *1.0E-05*, i.e. an algorithm is considered successful if it finds the error less than acceptable error in a given number of generations.

Parameter Estimation for Frequency Modulated Sound Waves Problem [1] was solved by number of researchers with the help of various algorithms. Recently S Das *et al.* [11] used Differential evolution using a neighborhood-based mutation operator to tackle this problem. A Rajshekhar et al. [12] make use of Levy mutated Artificial Bee Colony algorithm for global optimization to get rid of this problem. A novel approach namely Particle Swarm Optimization with Dynamic Local Search for Frequency Modulation Parameter Identification proposed by Y Zhang et al. [13] in 2012. Y. Lai et al. [14] proposed a new approach to automate the optimization of the parameters of a FM (frequency modulation) synthesizer with the help of genetic algorithm. S Ghorai et al. [15] developed a faster DE algorithm to automate process of parameter calibration for Frequency Modulated Sound Waves. S. Kumar et al. [9] gives a memetic approach in DE to find parameters in Frequency Modulated Sound Waves. Recently S. Kumar et al. [16] developed a new strategy using opposition based learning method and applied it to solve Parameter Estimation for Frequency Modulated Sound Waves Problem. Literature has large number of techniques to estimate parameters for Frequency Modulated Sound Waves.

## IV. PROPOSED SPIDER MONKEY OPTIMIZATION ALGORITHM

In order to get rid of Parameter Estimation for Frequency Modulated Sound Waves Problem this paper presents a novel and efficient approach using Spider Monkey Optimization algorithm. The newly proposed strategy is self adaptive in nature as it modify the position of local leader based on its current position. Its location based on present location linearly decline from 100 percent to 50 percent in every iteration. Based on the assumption that the solution of local leader phase will be far from the optimal solution in the $1^{st}$ iteration and it will. converge intimately to the optimal solution in afterward iterations and dynamically adjust position of local leader.

The proposed algorithm also modifies the process of position update in global leader. It use probability of selection of each individual to update modify the position.

It engender the new locations for the entire group members using Eq. (9) during local leader phase and Apply the greedy selection mechanism between existing position and newly computed position.

$$SM_{newij} = SM_{ij} + rand[0,1] \times (LL_{kj} - SM_{ij}) + (p_i) \times (SM_{rj} - SM_{ij})$$

Here $P_i$ is probability of selection. The probability $p_i$ ($p_i$ denote probability of $i^{th}$ solution) for every group member. Probability is calculated using fitness of individuals as per Eq. (10).

$$p_i = 0.9 \times \frac{fitness_i}{fitness_{\max}} + 0.1$$

During global leader phase it engenders new positions for the every member of group using Eq. (11).

**Algorithm 1: Position update of local leader**

If position of a Local leader is not updating after $LL_{Limit}$ then apply following steps.

if $U(0,1) > p_r$

$$SM_{newij} = SM_{\min j} + \phi \times (SM_{\max j} - SM_{\min j})$$

$$Where\ \phi \in (0,1)$$

else

$$SM_{newij} = SM_{ij} + rand[0,1] \times (GL_j - SM_{ij}) + (SM_{ij} - LL_{kj}) \times (\omega_{\max} - \frac{iter}{\max\_iter}(\omega_{\max} - \omega_{\min}))$$

$$SM_{newij} = SM_{ij} + rand[0,1] \times (GL_j - SM_{ij}) + (p_i) \times (SM_{rj} - SM_{ij})$$

In order to modernize the position of local leader it use algorithm 1.

**Algorithm 2: Adaptive Spider Monkey Optimization (ASMO) Algorithm**

Initialize all parameters
Calculate fitness
Choose leaders (global and local both)
Repeat till the extermination criterion is not fulfilled.
Generate the fresh locations for the entire group members

$$SM_{newij} = SM_{ij} + rand[0,1] \times (LL_{kj} - SM_{ij}) + (p_i) \times (SM_{rj} - SM_{ij}) \text{Here } p_i \text{ is probability}$$

Apply the greedy selection mechanism between existing position and newly computed position.
Compute the probability $p_i$ ($p_i$ denote probability of $i^{th}$ solution) for every group member.

$$p_i = 0.9 \times \frac{fitness_i}{fitness_{\max}} + 0.1$$

Engender new positions for the every member of group.

$$SM_{newij} = SM_{ij} + rand[0,1] \times (GL_j - SM_{ij}) + (p_i) \times (SM_{rj} - SM_{ij})$$

Modernize local and global leader's position.
If position of a Local leader is not updating after $LL_{Limit}$ then apply following steps.
if ($U(0,1) > pr$)

$$SM_{newij} = SM_{\min j} + rand[0,1] \times (SM_{\max j} - SM_{\min j})$$

else

$$SM_{newij} = SM_{ij} + rand[0,1] \times (GL_j - SM_{ij}) + (SM_{ij} - LL_{kj}) \times (\omega_{\max} - \frac{iter}{\max\_iter}(\omega_{\max} - \omega_{\min}))$$

If position of Global Leader is not updating after $GL_{Limit}$ then apply following steps.
if ($Global\_Limit\_Count > GL_{Limit}$ ) then
Set $Global\_Limit\_Count = 0$
if (Number of groups < $MG$ ) then
Divide the population into groups.
else
Merge all the groups into single large group.
Bring up to date position of Local Leader.

The value of $\omega_{\max}$ and $\omega_{\min}$ are preset to 1 and 0.5, in that order. The local leader's location based on existing location linearly dwindles from 100 percent to 50 percent in every round of experiment.

Position of global leader updated in same manner as basic SMO algorithm. The proposed algorithm summarized in algorithm 2.

The proposed algorithm relies on the idea that the solution of local leader phase will be distant from the best feasible solution in the 1st iteration and it will converge intimately to the most favorable solution in subsequent iterations, algorithm 2 will with dynamism regulate the location of local leader by allowing a spider monkey in the 1st iteration to stroll with a large step size in the search area. The step size for the wandering of spider monkey will decrease with increment in the number of the iteration.

## V. EXPERIMENTS

This paper validated the performance of the planned Adaptive Spider Monkey Optimization algorithm with the original technique in Parameter Estimation for Frequency Modulated Sound Waves Problem. The performance of newly proposed algorithm is compared with Basic SMO algorithm [1], Artificial Bee Colony Algorithm [17], Differential Evolution algorithm [18] and SMO's recent version MPU-SMO [3]. The performance compared based on standard deviation (SD), mean error (ME), average function evaluation (AFE) and success rate (SR).

Experiments are performed in C programming language with following experimental setup for ASMO.

- The size of swarm $N$ = 50 ( Number of Spider Monkeys at the time of initialization)
- $MG$ = 5 ( Maximum group limiting maximum number of spider monkeys in a group as $MG = N/10$)
- Global Leader Limit ($GL_{limit}$)=50,
- Local Leader Limit ($LL_{limit}$)=1500,
- $p_r \in [0.1, 0.4]$, linearly growing over iterations,

Remaining all parameters is similar to basic SMO algorithm [1]. Size of swam for ABC and DE also similar to ASMO. Experimental setup for ABC is as follow:

- The size of colony= Population size $SN$ =50
- Number of Employed bee or Onlooker bee = $SN/2$
- The maximum number of cycles for foraging =200000
- Number of repetition of experiment =Runtime =100
- Limit =1500, A food source which could not be improved through "limit" trial is abandoned by its employed bee.

Experimental setup for DE is as follow:

- Population Size $NP$ = 50 and the Scale factor $F$= 0.5

- Limit = *D**NP*/2 and Number of Run =100
- Sopping criteria is either reached the corresponding acceptable error or maximum function evaluation (which is set as 200000).
- Crossover probability *CR* = 0.5.

## VI. Results And Discussion

The results obtained with basic SMO, MPU-SMO, basic ABC, basic DE and proposed ASMO are reported in table I. Table I discuss results in terms of Success rate, average number of function evaluations, mean error and standard deviation.

Table I. Comparison of the Results of ASMO for Parameter Estimation for Frequency Modulated Sound Waves Problem

| Algorithm \ Measure | Standard Deviation | Mean Error | Average Function Evaluation | Success Rate |
|---|---|---|---|---|
| **ASMO** | 3.59E+00 | 1.51E+00 | 43768.3 | 84 |
| **SMO** | 6.00E+00 | 7.07E+00 | 182324.8 | 37 |
| **MPU-SMO** | 4.92E+00 | 4.18E+00 | 82001.6 | 72 |
| **ABC** | 4.76E+00 | 9.16E+00 | 198494.7 | 1 |
| **DE** | 6.21E+00 | 4.64E+00 | 89742 | 61 |

It can be observed from table I that proposed ASMO algorithm achieve better success rate in comparison to considered other algorithms. The ASMO algorithm is also able to achieve optima in less number of function evaluations. Additionally, the speed of convergence for the considered algorithms also computed with the help of AFE. It is considered that the less number of AFE indicate that the algorithm has higher rate of convergence. The SMO algorithm is stochastic in nature. So as to diminish the significance of this stochastic nature the measured AFEs for all algorithms averaged over 100 runs for considered problem. Acceleration Rate (AR) computed in order to check rate of convergence. Acceleration Rate (AR) is defined as follows based on the AFEs for the two algorithms ALGO and ASMO:

$$AR = \frac{AFE_{ALGO}}{AFE_{ASMO}}$$

Here $ALGO \in \{SMO, MPU-SMO, ABC, DE\}$. The AR>1 indicates that ASMO has higher rate of convergence. Comparison of rate of convergence for ASMO-SMO, ASMO-MPUSMO, ASMO-ABC and ASMO-DE reported in table II. It can be observed from table II that ASMO algorithm always has higher rate of convergence.

Table II. Acceleration Rate (AR) of ASMO Compare to the Basic SMO, MPU-SMO, Basic ABC and Basic DE for Parameter Estimation for Frequency Modulated Sound Waves Problem

| Algorithm | Acceleration Rate |
|---|---|
| **SMO** | 4.165682 |
| **MPU-SMO** | 1.873539 |
| **ABC** | 4.535125 |
| **DE** | 2.050388 |

## VII. Conclusion

This paper proposed a novel approach for Parameter Estimation for Frequency Modulated Sound Waves Problem by modifying basic Spider Monkey Optimization algorithm. This approach add probability based position update in global leader phase and dynamically decrease size of search radius for local leader with advancement in iterations and named as Adaptive Spider Monkey Optimization algorithm. The proposed ASMO algorithm easily solved the considered problem with great success rate and with less number of function evaluations i.e. with higher rate of convergence. Convergence rate of ASMO is four times of convergence rate of basic SMO and basic ABC. It is almost two times in comparison to MPU-SMO and DE algorithm.

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