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Medical Pattern Matching Using Constrained Squirrel Search Algorithm

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Abstract: Medical pattern matching plays an essential role in our daily life, as each individual depends on that in a number of the other aspects. To realize higher and economical results the method itself is carried out in multiple phases. The pattern matrixes that hold the relation between the variables and therefore the factors that are generated by the Squirrel Search formula are studied and appropriate techniques are utilized for pattern recognition. This paper concludes with results and discussions of the optimisation algorithms, at the side of a artistic movement scope of the formula within the medical pattern recognition and matching. This paper also proposes an enhancement of the Squirrel search algorithm (SSA)[5] by extending it for constrained optimization problems. This Squirrel search algorithm is initially benchmarked on a group of test issues together with CEC2014 [7] to check and verify its performance. SSA works by imitating the dynamic search behavior of southern flying squirrels as well as their effective locomotion method called gliding. Although the prevailing Squirrel Search formula has proven to be a lot of correct and per exceptional convergence behaviour compared with the opposite reported optimizers, the formula isn't yet enforced for resolution affected consistent with issues. this will be achieved by introducing constraints and call variables to the prevailing formula and validation of a similar with a selected set of affected benchmark functions.

Keywords: Nature inspired algorithm, SSA, CEC2014, Medical Pattern Recognition.

1. INTRODUCTION

The process in which we find the best values for the variable of a given problem minimizing or maximizing a particular objective function is known as optimization. To solve an optimization problem, series of steps are involved. Initially the parameters of the given problem is to be identified. Depending upon the nature of parameters, the problems could be either continuous or discrete. The second step is applying the constraints on the parameters identified. Constraints can either constrained or unconstrained. Next the objectives are investigated. After which the problems are classified into single versus multi objective domain. After all these processes, depending upon the parameters identified, constraints and objectives one suitable optimizer technique should be chosen and employed in order to solve the problem specified.

The algorithms inspired by Nature [1] can be divided into three key categories: evolutionary algorithms (EA), swarm intelligence (SI), physics based algorithms. The Squirrel Search algorithm belongs to the swarm intelligence based nature inspired algorithm. One important feature about flying squirrels is that they avoid flying .Instead they use the gliding mechanism which in comparison with other mechanism is energetically cheap, and efficient for allowing small mammals to cover large distances in a quick and efficient way. The study also indicates that predator avoidance, optimal foraging, and foraging costs are the main cause of gliding evolution. By displaying a dynamic foraging behavior, the squirrels can make optimal use of food resources. In order to meet the nutritional requirements in autumn season, the squirrels tend to eat acorns (a mast nut) as they are available in high quantities and store all other types of nut. In the winter season the hickory nuts are eaten once it is seen due to the high foraging cost at low temperatures. Therefore, what the flying squirrels do is that they selectively eat some nuts and store others which varies based on the nutritional demands. The primary source of motivation for the suggested SSA is this intelligent dynamic foraging behavior of southern flying squirrel. The gliding mechanism of flying squirrels is modelled mathematically in this dynamic foraging strategy of work and restrictive handling mechanisms are introduced [1][3][4] to build SSA for restricted.

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2. LITERATURE SURVEY

The search begins once once squirrels begin hunting. thro ughout the hot weather (autumn). The squirrels seek for food resources by flying from one tree to the opposite. Whereas doing thus, they modify their location and explore different areas of forest. throughout winter, a loss of leaf cover in deciduous forests results an increased risk of predation and therefore they become less active but don't hibernate in winter. At the top of winter season, once squirrels becomes active again. This method can be a repetitive process and hence persists over a period of time of a once squirrel and forms the inspiration of SSA. The assumptions that are considered for simplification of are as follows:

1. n number of flying squirrels are tree in a deciduous forest and only one squirrel is assumed to be on a tree at a time.
2. Each squirrel searches for food individually and uses the available food resources in an optimal way by demonstration of a foraging attitude.
3. It is assumed that there are only 3 kind of tree available in the forest.

Such as normal tree, oak tree which are a source of acorn nuts and hickory tree which is the source of the hickory nuts .

4. For now the forest is assumed to have 1 hickory trees and 3 acorn trees. Here, the value of n is assumed to be 50. There are 4 nutritious food resources (N_{fs}) out of which 1 is hickory nut tree and the remaining 3 are acorn nut trees, whereas the other 46 trees don't have any food source. Which means 92% of the total squirrels exist on normal trees, while all the other population in on any tree with a food source. We can also vary the no. of food resources as per the constraint $1 < N_{fs} < n$ where $N_{fs} > 0$ with one optimal winter food source.

The algorithm proposed works on implementing SSA for constrained optimization problems. The results achieved show that the SSA offers more precise solutions with a high convergence rate relative to other existing optimizers in the rest.

3. PROPOSED SYSTEM

3.1 Problem Definition

To develop a Squirrel Search Algorithm[SSA] for solving constrained optimization problems and compare the results with the existing algorithms.

3.2 Algorithm

1. Define the input parameters
2. Generate random locations for n number of flying squirrels
3. Evaluate fitness of each flying squirrel's location
4. Sort the locations of flying squirrels in ascending order depending upon their fitness value
5. Declare the flying squirrels on hickory nut tree, acorn nuts trees and normal trees
6. Randomly select some flying squirrels which are on normal trees to move towards hickory nut tree and the remaining will move towards acorn nuts trees while(the stopping criterion is not satisfied)
7. For t =1 to n1 (n1=total flying squirrels which are on acorn trees and moving towards hickory nut tree)

if $R1 \geq P_{dp}$

$FS^{t+1}_{at} = FS^{t}_{at} + d_g \times G^{c} \times (FS^{t}_{ht} - FS^{t}_{at})$

else

FS^{t+1}_{at} =a random position of search space

end

end

8. For t=1 to n2 (n2=total flying squirrels which are on normal trees and moving towards acorn trees)

if $R2 \geq P_{dp}$

$FS^{t+1}_{nt} = FS^{t}_{nt} + d_g \times G_c \times (FS^{t}_{at} - FS^{t}_{nt})$

else

FS^{t+1}_{nt} =a random position of search space

end

end

9. For t=1to n3 (n3=total flying squirrels which are on normal trees and moving towards hickory nut tree)

if$R3 \geq P_{dp}$

$FS^{t+1}_{nt} = FS^{t}_{nt} + d_g \times G_c \times (FS^{t}_{ht} - FS^{t}_{nt})$

else

FS^{t+1}_{nt} =a random position of search space

end

end

10. Calculate seasonal constant(Sc)
11. if(Seasonal monitoring condition is satisfied)

Randomly relocate flying squirrels end Update the minimum value of seasonal constant (Smin)

end

12. The location of squirrel on hickory nut tree is the final optimal solution end

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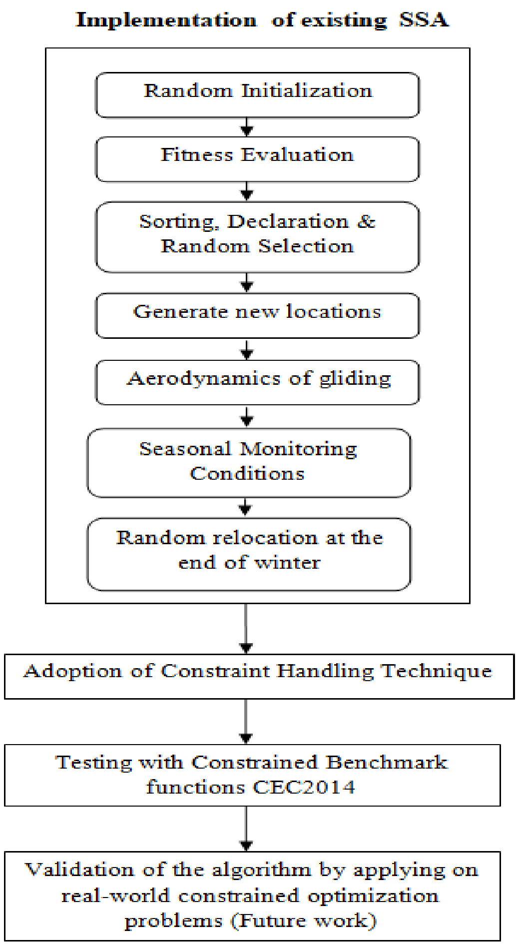
3.3 Architecture Diagram



3.4 Module Description

3.4.1. Implementation of the existing algorithm

1. The distance can be sensed by the Squirrel using the echolocation and they also sense the distance between food and the barriers(predators).
2. The velocity of the squirrel represented by V_i and position of the squirrel by X_i having frequency F_{min} with varying wavelength and loudness A_0
3. The loudness A_0 also takes a min constant value.

Step 1: Firstly the statement for squirrel function is made.
[bestfit, bestPositions, f_{min}, Convergence_curve] = squirrel (N,Max_iter,lb,ub,dim,f_{obj}) (1)
In above statement the input parameter is mainly a benchmark function which is represented by a 'f_{obj}' and others are lb=lower bound limit and ub=upper bound limit, f_{max} is the maximum frequency and f_{min} is the minimum frequency , A= loudness of each squirrel, r=pulse emission rate of each squirrel, alpha and gamma are the constants for the loudness and pulse emission rate. The r_0 is the initial pulse rate.

Step 2: After the statement, the initialization function is called.
x=initialization(N, Max_iter, dim, ub, lb) (2)
In initialization state, upper bound and lower bound limits are already available and position of the squirrel position is randomly generated. Each squirrel has different upper and lower bound limits. There is N number of searching variable. The initial position of the search variable is calculated. The parameters of algorithm are initialized, and then the best solution in the population are determined. Here, virtual squirrels are moved in the search space according to updating rules of the SSA algorithm.

Step 3: The benchmark function is which is represented by the 'f_{obj}' is defined and the initial best fitness value for benchmark objective function is found. The f_{obj} function contains all the information about the benchmark function.
Here, 23 different benchmark function[6] cases which have different dimensions, upper bound and lower bound limits have been chosen. The initial best value is obtained using
[f_{min}, index]=min(fitness) best initial fitness value
Also the best solution for the best fitness value of the objective function is found.

Step 4: Then the main loop for the maximum iterations is started. The velocity of the squirrel and position of the squirrel is updated. After the update, the upper and lower bound limits are applied and the position of the squirrel is updated again.

Step 5: The condition of pulse rate emission of each squirrel (r) is checked

Step 6: The best fitness value after optimization is calculated. The convergence curve according to the best fitness value and iteration is calculated. The best position is also obtained through the optimization.
F min =fitnessnew (10)

Step 7: Another script for the observation of benchmark function is written. The parameters like N=number of searching squirrels, any benchmark function are defined.

3.4.2. Implementation of SSA for constrained optimization problems

The proposed algorithm details are explained in detail below:

1. Initialization of the number of search agents, food sources, upper and lower bound ranges are done.
2. Fitness value of each squirrel is calculated.
3. New locations of the squirrel is generated using zero force method.

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4. When new flying squirrel positions are created, the new location can be worse than the old one. This implies that after creating new positions the fitness value of each person needs to be tested by comparing with the old one in each iteration. If the fitness value of the new position is higher than the old one, then the new position will change the position of the corresponding flying squirrel. Otherwise the old posture is retained. Hence it is important to sort the flying squirrel's positions.
5. Another script for benchmark function is written. The parameters like N=number of searching squirrels and the upper and lower bound values are defined for all the 23 benchmark function
6. The best fitness value will be calculated after optimization. The convergence curve is plotted according to the best fitness value and iteration. Even, it gets the best position.

There are four strategies [9] incorporated to enhance the algorithm's global search capability. This summarizes the strategies as follows:

(i) An adaptive strategy is proposed for the probability of predator existence, which changes dynamically with the iteration process. This strategy discourages premature convergence and enhances the algorithm's intensive search capability, particularly at the latter stages of search. In this way, a balance between the exploration and exploitation capabilities can be properly managed.

(ii) The proposed algorithm uses a normal cloud generator to create new flying squirrel locations during the gliding process, thus enhancing SSA's exploration capability. This is inspired by the fact that the gliding behaviors of flying squirrels have unpredictable and fuzzy characteristics, which the usual cloud model can explain simultaneously

(iii) A selection strategy between successive positions is proposed to maintain the best position of a flying squirrel individual throughout the optimization process, which enhances the exploitation ability of the algorithm.

(iv) Originally, a dimensional search enhancement approach is put forward and results in improved quality of the best solution for each iteration, thereby improving the algorithm's local search capability.

4. RESULT ANALYSIS

1. The proposed algorithm is proved to be more efficient than the existing work since it yields the best optimal solution for all the benchmark functions which lacks in the existing optimizers.
2. The algorithm yields the best result global best solution in less number of iterations than the existing algorithm.
3. The existing algorithm never converges to a solution when the number of iterations are increased but the proposed algorithm is not so.

The results of the existing and proposed algorithm are compared below.

Table 4.1 Comparison of execution time of the optimizers

Function name	Unconstrained optimization algorithm (in seconds)	Constrained optimization algorithm(in seconds)
F 1	2.323	0.855
F 2	3.181	1.012
F 3	2.442	0.869
F 4	2.473	0.934
F 5	3.218	0.891
F 6	2.497	0.886
F 7	2.985	1.211
F 8	2.758	1.208
F 9	3.091	1.275
F 10	3.267	1.278
F 11	2.698	1.177
F 12	4.041	1.235
F 13	3.128	1.201
F 14	-	2.597
F 15	3.951	2.594
F 16	3.335	1.482
F 17	3.370	1.444
F 18	3.662	1.315
F 19	-	0.770
F 20	-	0.776
F 21	-	1.547
F 22	-	0.991
F 23	-	1.773

Table 4.1 shows that the execution time of the proposed algorithm is comparatively less than that of the existing one.

The performance of both the algorithms are compared on 23 standard classical benchmark functions implemented by many other authors for evaluation as it consists of both unimodal (F1-7) benchmark functions, multimodal (F8-13) benchmark functions and fixed dimension multimodal (F14-23) benchmark functions. As it is proven that evaluation of an algorithm against unimodal functions show the efficiency of exploitation property and multimodal functions show the efficiency of exploration property, they are used here for performance analysis. The resultant graphs obtained for each of the benchmark function for both the algorithms is shown below.

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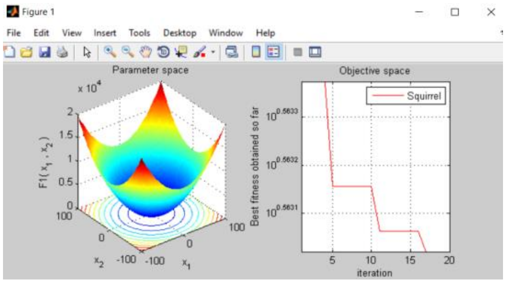
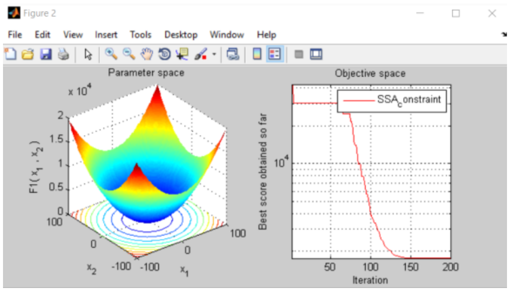
Fig 4.2 Convergence Curve for benchmark function F1(unimodal)

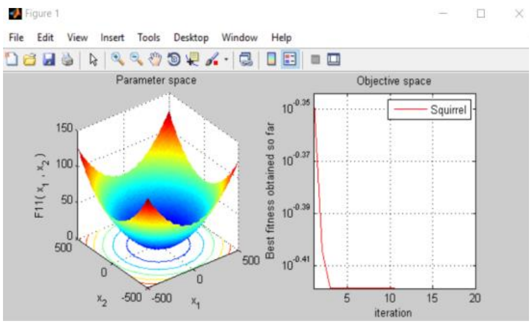


4.2.1Unconstrained optimization algorithm

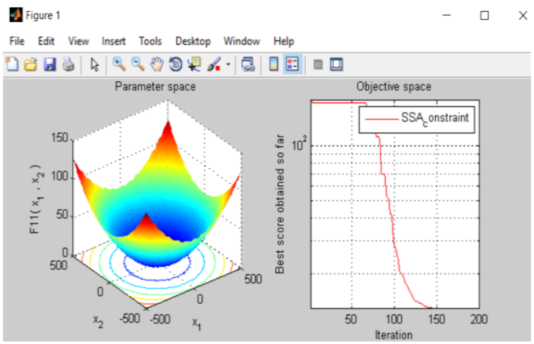


4.2.2 Constrained Optimization algorithm

Fig 4.3 Convergence curve for benchmark function F11 (Multimodal)

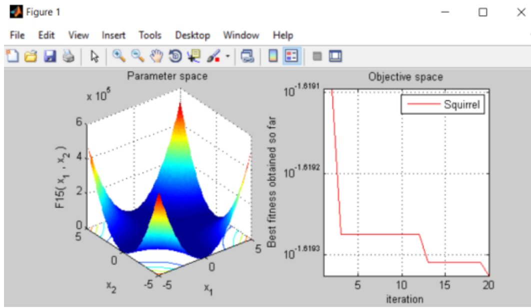


4.3.1 Unconstrained Optimization Algorithm

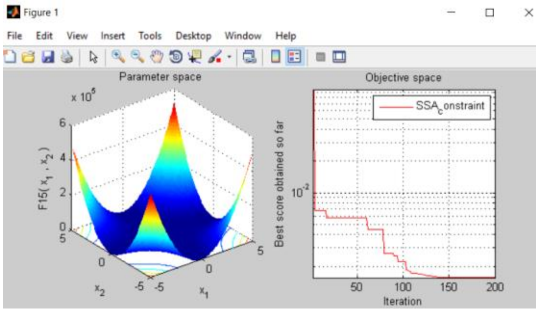


4.3.2 Constrained Optimization Algorithm

4.4 Convergence curve for benchmark function F15(fixed dimension multimodal function)



4.4.1 Unconstrained optimization algorithm



4.4.2 Constrained Optimization algorithm

It was also observed that the unconstrained optimization algorithm suffers from premature convergence for a set of benchmark functions(F19, F20, F21, F22, F23)

5. MEDICAL APPLICATION

The implementation of Squirrel Search algorithm generated certain pattern matrices depicting the correlation between the variables and the factors. Pattern Matching process can be done by recognizing the patterns from the pattern matrices that are generated by the algorithm. Each and every row of the pattern matrix is a regression equation in which the observed standardized variable is denoted as factor function. This pattern matching system finds its applications in various medical fields especially for analyzing test results in decision support for any illness. The algorithm employs 5 steps for the pattern analysis in order to generate the pattern matrix

Step 1: Selection and measurement of a set of variables from a specified domain.

Step 2: Screening of data for preparing the correlation matrix.

Step 3: Extraction of relevant factors..

Step 4: Rotation of factors to increase the interpretability.

Step 5: Interpretation.

The patterns may be a image of a fingerprint, word handwritten, face of a human, signal of speech, sequence of DNA etc.. Besides this Pattern recognition also has its roots in artificial intelligence (AI). It is the study of ability of machines that learn to distinguish patterns and make some decisions about the pattern and its related categories. These patterns can be recognized from the pattern matrices with the help of fuzzy logics [8]. The fuzzy sets' importance in Pattern Recognition can be done by modeling the forms of uncertainty which can be completely understood by the use of theory of probability. Syntactic strategies are highly in use when the patterns sought are linked to the formal language structure. They are used when generating fuzzy partitions of the data sets.

These recognized patterns can be employed in Clinical decision support systems (CDSS) in which one of the first successful applications of Artificial Intelligence, focusing primarily on the diagnosis of the condition of a patient is done when his symptoms and demographic information are given. A rule based expert system called Mycin3 for diagnosis of diseases was employed along with The Clinical Decision Support System for medical diagnosis work in the early 1970's.

6. CONCLUSION

This work proposed an enhancement to the Squirrel Search Algorithm (SSA) by extending it for constrained optimization problems. The following observations have been made after comparing the result of the proposed work with the existing optimizer.

- The convergence curve of the proposed algorithm shows that the algorithm fetches result for all the iterations without any stagnation of values.
- The execution time of the proposed algorithm is comparatively lower than that of the existing algorithm.
- The proposed algorithm doesn't get trapped in any local optimum.
- The global optimal value is reached in less number of iterations for the proposed algorithm than the existing optimizer.

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