Optimization of the Database Function Transactions by using the Fireworks Algorithm

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Abstract. Inspired by the fireworks flare-up at night, the old algorithm of fireworks (FWA) developed during 2010. Since then there have been some changes or unfinished programs intended to enhance FWAS affectivity. The conventional fireworks algorithm is a forward summary and reviewed in this article, or is presented below three elevated fireworks algorithms. By swapping the methods for numbers measured and instead of the amplitudes of the sparks between the Outbreak of fireworks, the high FWA algorithms turn out to be more lifelike or explainable. The multi-purpose fireworks algorithm, although the image processing (GPU) designed fireworks algorithm is provided as well, the GPU mostly based the algorithm of fireworks is capable of speeding up the optimization. Large experiments on thirteen benchmark services show that the sum of the 3 algorithms multiplied by fireworks dramatically increases the propriety of found solutions but strongly decreases the walking time. Lastly, the fireworks algorithm's limited capabilities are concisely defined, while its inadequacies are acknowledged, then future lookup advices.

1. Introduction

Some problems that remain simplified in near-Database fields, including Problems around numerical optimization By modelling mathematics. Half of the issues—not just the most efficient solution, however, also more than one feasible solutions and the best localized workable solutions must be characterized by decision-makers after sufficient knowledge has been provided. In general, those issues are known as multi-modal then multi-objective problems of optimization. For the purpose of solving these problems, in the simulation of stand located out, the most and the minimum values on the facilities like.

Conventional approaches often describe a differentiable and continuous feature by using slope knowledge based mathematical methods. Longevity. However, traditional approaches can not always get even rational solutions When tackling multi-modal and multi-objective problems of optimization. Recently, several output algorithms are advised to solve feature optimization problems professionally. Learning the biological phenomenon is not only compulsory in the field of biology but also applied to Computer technology, mathematics, The science of knowledge, and more fields of study. In the of computer science field, many swarm intelligence (SI) algorithms are developed, encouraged through animal behavior. Swarm in adjacent zones can be viewed as multiple individuals, and there is contact between them.
An ant, or a bee, or a bird will barely survive without their clan in Nature. Consequently, a community of organics, like the birds mentioned above, ants or bees, have extra chances of staying alive than the lone person. The probability of survival is a hard structure of the chance of each individual, but a more informative description of the social and community dynamic.

The nature of animal group will help their individuals adapt considerably to the climate. Specific information is collected separately from gregarious interaction and information which have been obtained by a person in a group is greater than the information that any person is capable of obtaining alone. The information which is transferred between the group, and every process has modified this transferred information, including its behavioural patterns. The entire community therefore has some features and skills, particularly the ability to adapt to their situation, which can hardly be acquired by a single person while operating alone. An individual's ability to adapt according to climate is known as intelligence, obtained by individual clustering. Moved by definition, it proposes many algorithms of swarm intelligence.

Seeing the technique used by ants to find food, the Colomi and his partners suggested the algorithm of the ant colony optimization (ACO) [1]. In addition, Kennedy and Eberhart have suggested the algorithm of the Particle Swarm Optimization (PSO) [2]. This algorithm mimics birds flight patterns to capture food. However, the differential evolution (DE) algorithm is just an additional algorithm of the swarm intelligence that Storm and Price put forward [3]. This algorithm, the distinction between individuals is used to the max. It has proposed the recently declared fish school search (FSS) algorithm and artificial bee colony (ABC) algorithm [4]. A SI algorithm which has been provided by Tan and Zhuis the latest recommended fireworks algorithm (FWA) [5].

This algorithm has been inspired by an eruption of fireworks at night, and is very successful in finding maximal global value. A shower of sparks is seen in nearest field, as a firework explodes. Those sparks will erupt again in a smaller area and produce many shows of several sparks. Gradually, in a fine structure, the sparks perform the searching for the entire solution space and settle on a specific area for finding the optimum solution. The FWA will fulfill 3 user requirements as a realistic optimization algorithm [3]. Next, FWA will process functions for linear, nonlinear, and multi-model testing. Second, to cope with dynamic functional problems, FWA can be parallelized. Second, FWA has properties of good convergence and can still consider global minimization.

This paper fully analyses the algorithm of the fireworks, counting the algorithm of the traditional fireworks, its enhancements and its implementations. Each algorithm is evaluated on standard data-sets. The rest of the article has been written as follows. Section II introduces the standard algorithm for the fireworks. Via various academics Section 3 describes three innovations. Some experiments are planned, and the results of the experiments are shown in section 4. In the final section 5, further directions and conclusions for research have been drawn to expand the research and broaden the application spectrum of the firework algorithm.

2. Fireworks Algorithm

The sparks have emerged round a site after a fireworks exploded. Explosion operation may be viewed as searching the surrounding region that surrounds a certain location. Inspired by the real-world fireworks, it proposes the Fireworks algorithm (FWA). In each generation, FWA uses N D-dimensional parameter Vectors xG as the primary population. The parameter I differed from 1 to N, and parameter G is generation index. Each single person in population 'explodes' plus produces sparks around him / her. Specific methods decide the amount of sparks, and the intensity of every event. Now, the Gaussian explosion is utilized in order to create sparks and preserve populace diversity.
Ultimately, the algorithm retains the superior person in population and chooses the remaining
(N – 1) persons which have been created for the next generation on space. For the fireworks
algorithm more complex strategies is described as shown next.

2.1 The Strategy of Explosion Sparks
The technique of the explosion sparks is mimicking the fireworks explosion, which is basic
policy in the FWA. The spark vanishes as spark explodes, and numerous sparks emerge
surrounding it. The technique of the explosion sparks is mimicking that phenomenon is applied
through the explosion to create new people. Two criteria needed to be settled in this strategy.
The initial one is the number of sparks,

\[ S_i = S \cdot \frac{Y_{\text{max}} - f(X_i) + E}{\sum_{i=1}^{N} (Y_{\text{max}} - f(X_i)) + E} \]  (1)

In the formula, Si means the quantity of sparks generated from the population through a single,
wherever I differs from 1 to N. It is set as a constant as one of the controlling parameters of the
entire number of sparks produced. Suppose that the aim is finding the minimum of one element.
Variable Ymax represents the current generation’s lowest fitness value, while f(Xi) represents
the fitness value for a person Xi. To stop the denominator from ending in zero, the latest
parameter specified as γ is added. The other parameter in this technique is spark amplitude.

\[ A_i = A \cdot \frac{f(X_i) - Y_{\text{min}} + E}{\sum_{i=1}^{N} (f(X_i) - Y_{\text{min}}) + E} \]  (2)

Ai variable provides the amplitude to produce the explosion sparks for an individual Xi, and A is
a constant regulating the amplitudes. Amplitudes are measured with the finest fitness factor
Ymin. The last parameter in this formula tends to escape the mistake of making the denominator
becoming zero. In the event that an person is near boundary, the sparks produced that lie outside
available space. A visualization approach is then employed to save sparks in the open field.

2.2 Mapping Strategy
The mapping technique guarantees that people live in the room available, in the case where
there are any sparks out of the boundary then they are mapped to their proper distance.

\[ X_i = X_{\text{min}} + |X_i| \% (X_{\text{max}} - X_{\text{min}}) \]  (3)

Where Xi means the locations of other sparks lying outside borders, where X_max and X_min
denotes a spark spot’s maximum and minimum limits. The percent symbol represents the
Arithmetic’s modular operation. Besides the explosion spark method, another method of
generating sparks has been suggested as a Gaussian spark strategy.

2.3 Gaussian Sparks Strategy
The Gaussian sparks method has been utilized to produce sparks with the Gauss distribution,
so as to preserve population diversity. Suppose the current individual’s position is specified as
X k^j, the Gauss Sparks from the explosion are estimated as

\[ X_k^j = X_k^j \cdot G \]  (4)

G represents a random number in the Gauss distribution.

\[ G = \text{Gaussian (1,1)} \]  (5)

Gaussian distribution binds by parameter g. After frequent explosions and Gauss explosions,
we are finding an appropriate way to choose the next generation of individuals. A distance
dependent method of selection has been proposed here.
2.4 Selection Strategy

Now the best person is often held at first to pick the individuals for next generation. So the following distance \((N-1)\) is used as the basis for individual selection. Individuals who are far from other individuals get a better chance of being selected compared to the individuals with smaller ranges to other people. The overall distance between 2 locations is determined according to

\[
R(X_i) = \sum_{j \in K} d(X_i, X_j) = \sum_{j \in K} ||X_i - X_j||
\]  

(6)

Where \(X_i \& X_j\) (ij) positions may be any location, and \(K\) represents the set of all of the current locations. Several methods like the Manhattan, Euclidean, and Angle-based distances are used for distance measurements. Motivated by immune density (Lu, Zhao and Tan 2002), the fireworks algorithm uses Euclidean distance (Tan, & Zhu, 2010).

\[
d(X_i, X_j) = | f(X_i) - f(X_j) |
\]  

(7)

Where \(f(X_i)\) is position fitness \(X_i\), \& \(d(X_i, X_j)\) stands for the difference between 2 locations. Finally, the probability of selecting the locations is determined using a roulette wheel process.

\[
P(X_i) = \frac{R(X_i)}{\sum_{j \in K} R(X_j)}
\]  

(8)

Individuals with wider distances from others have better odds of being selected. This approach ensures that demographic diversity can be assured.

Fireworks algorithm function well at the following parameters, where \(a=0.04, b=0.80, n=5, m=50, A = 40\) and \(m\) as well = 5. While at many issues the fireworks algorithm makes considerable progress, there are still some areas for enhancement. Zheng y al. (Janecek, Tan, and Zheng 2013) suggested an improved FWA that enhanced the test function results’ accuracy significantly. Liu et al. (Liu, Tan, and Zheng 2013) researched the fireworks algorithm’s discovery and processing capabilities, and later developed a transfer function for the purpose of measuring sparks number and amplitude. Pei et al. (Pei, Zheng, Tan, & Takagi, 2012) gave an experiential analysis about the impact of multiple fireworks algorithm fitting approaches. Other related guidelines that include but are not limited to (Zhou, & Tan, 2009), (Bureerat, 2011), (Zhou, & Tan, 2011), and (Lou, et al 2012).

3. Enhanced Fireworks Algorithm (EFWA)

To address the drawbacks of the FWA, several researchers made the attempt to develop it in various ways. Zheng et al. (Zheng, Tan, and Janecek 2013) have suggested an improved FWA by improvements in the following 5 functions.

3.1 Minimum Explosion Amplitude Setting

In a course of evolution, multiple amplitudes of explosions may be approximate to 0, which isn’t helpful in finding the finest global value. As the magnitude of the explosion has been tightly associated with the fitness values, two methods were suggested to restrict the boundary of the minimal amplitude. A single method has been based upon a linear function, and a non-linear function is based on the other.

\[
A_{min}^k(t) = A_{init} - \frac{A_{init} - A_{final}}{evals_{max}} * t
\]  

(9)

\[
A_{min}^k(t) = A_{init} - \frac{A_{init} - A_{final}}{evals_{max}} * \sqrt{(2 * evals_{max} - t)}
\]  

(10)
For both formulae, if the function is evaluated $t$ times, $A_{\text{min}^k}$ implies the minor boundary for an entity in $k$ dimension. The two separate $A_{\text{init}}$ and $A_{\text{final}}$ parameters stand for starting and the final amplitude values. The most recent parameter is cumulative evaluation times that are represented as $\text{evals max}^{-1}$. The diagrams for the linear and the nonlinear minimum amplitude values of explosions have been shown below.

![Diagram of Ainit vs Afinal with evaluations](image1.png)

(a) Linear decrease  
(b) Non-linear decrease

**Figure 1.** The diagrams of the minimum amplitude for linear and the nonlinear decreases. [6].

### 3.2 Explosion Sparks Strategy

The same increase in the fireworks algorithm is going to be applied to the different dimensions of a Person. The corresponding increase can cause a population to lose its diversity. Henceforth, for a person to obtain the variety of population, it is important generating various increment values and adding the increments to every one of the chosen dimensions.

### 3.3 Gauss Sparks Strategy

The FWA operates fine on functions which are at the origin of the coordinate will reach their optimum. The optimum 2-dimensional Ackley function value, for example, lies at the root of their coordinate. However, in the case of the shifting of feature, for example the optimum value is changed to [-60, -50], the algorithm for the fireworks performed poorly. The following figure illustrates the position of Gaussian sparks in the algorithm for fireworks. It has been shown that when the function is not modified Gaussian sparks might easily discover the ideal value at a source of the coordinate. Gaussian sparks nevertheless work unwell on shifted feature.

![Diagram of Gaussian sparks](image2.png)

(a) Optimal at origin  
(b) Shifted optimal value

**Figure 2.** Effect of the Gaussian sparks [6].
3.4 Mapping Strategy
The FWA being projected utilized the modular arithmetic operation for mapping the individuals back to the scope. Even so, a modular arithmetic operation takes time. In fact, certain people are assigned to a location close to birth, straying from population diversity. For example, supposing space for the solution differs between -20 and 20. In the case where the individual has a -21 value, then it will map to 1 based on the recommended formulation in the FWA. Then it introduces a new operator of mapping.

\[ X^k_i = X^k_{\text{min}} + \text{rand}(0,1) \times (X^k_{\text{max}} - X^k_{\text{min}}) \]  

Where \( X^k_{\text{min}} \) and \( X^k_{\text{max}} \) are the lower and upper boundaries of solution space, respectively.

3.5 Selection Strategy
Selection is the most time consuming aspect of modern FWA. In the traditional fireworks algorithm selection strategy, it is necessary to calculate the distances between individuals. Hence, the selection strategy's computational complexity is considerably greater than the strategy of the random selection. The process of selection is referred to as the Elitism Random Selection (ERS)[7]. For the next generation the best one of the individuals is still retained while the other (N-1) individuals are randomly picked. Thereby, the running time for the fireworks algorithm is highly reduced, and the complexity of computation is linear.

4. Comparison
Comparison is made of six swarm intelligence algorithms, which include the traditional FWA, 4 enhanced FWAs and SPSO algorithm. The SPSO algorithm parameters are identical to those of Bratton identical same parameters as the standard reference algorithm (Tan&Zhu, 2010). EFWA has been suggested by Zheng (Zheng, Tan, and Janecek 2013), while enhanced fireworks algorithm with fitness value selections (IFWAFS) and enhanced best-choice fireworks algorithm (IFWABS) may be observed in comparison (Liu, Tan, & Zheng 2013). LS2-BST10 algorithm has been the optimal algorithm which has been mentioned in the paper (Pei, et al, 2012) with the number of samples extinguished and the correct techniques. LS2-BST10 indicates that the sampling approach is nonlinear, with the collection of the finest ten individuals. To make the figures easier to read, the findings of the experiment are divided to 2 figures, which are, Fig. 5a and Fig. 5b. Hence, in Figure 5(a), the horizontal and vertical axis has a similar meaning as in Fig. 5b. The horizontal axis lengthwise denotes the 6 algorithms with 13 functions, and vertical axis characterizes the logarithm-shaped average values. Since the corresponding mean values are below zero, some bar figures are not shown, and the operation of the logarithm cannot be achieved.
From the above experimental results, the following observations can be determined.

- EFWA, IFWABS, IFWAFS and LS2-BST10 for most functions have been superior to the standard FWA.
- EFWA succeeds in much better performance with increasing shifted values than conventional FWA.
- EFWA continuously performs; even the maximum has been adjusted to the usable space edge.
- On substantially modified indexes, SPSO achieves better results;
- Improved algorithms for fireworks, including the EFWA, IFWABS, IFWAFS and LS2-BST10, For most of the tasks, worse than SPSO.
- EFWA has been enormously fast on 11 functions whereas the SPSO has been faster on two different tasks than other algorithms.
- The classical FWA needs significantly more time compared to all of the rest of the algorithms.

5. Future Directions and Conclusion
The algorithm for fireworks offers a whole new method of solving hard problem. The latest firework algorithm and its implementations show that it is capable of effectively solving various optimization issues. The firework algorithm can also be ideal for solving large data problems. The fireworks algorithm is worth investigating for theoretical or applied science, and can offer great scientific and economic advantages. But the fireworks algorithm also has some drawbacks.
First, the fireworks algorithm simulates biomes behaviour and lacks the requisite mathematical basis. For example, the fireworks algorithm does not display convergence. Secondly, experience sets the majority of the parameters in the FWA, and the parameters depend highly on unique issues. Third, there aren't many fireworks algorithm programs currently in use. Therefore, to fully understand its advantages, it is important to test any algorithm in real-world, instead of purely theoretical circumstances. The algorithm for fireworks has been significantly developed but it's not perfect yet.

Leading the way One may define future developments as follows. The fireworks algorithm first of all desires its logical and theoretical basis. Secondly, the fireworks algorithm's set of control parameters also relies on practice. So how to pick the most suitable parameters includes guidance from academia. Third, the predictions of applications of fireworks algorithms are still in infancy and need more researches. Fourthly, the FWA can learn from other algorithms, as an open-source algorithm. How to refine the algorithm for the fireworks is also a useful path for analysis. GPU's study to expedite the firework algorithm is at its initial steps and will be attracting other and new researchers who are dedicated to applying the algorithm of fireworks to the issues of the real world.

6. References

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