A Bio-inspired Techniques for Medical Images: Systematic Review

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***Abstract*—**the need to apply security approaches for medicinal pictures has expanded with the use of broadcast communications advances for restorative analysis and patient consideration once the supplier and customer are isolated by separation. Something alluded to as telemedicine is found in such cases. Telemedicine is imperative as it empowers meetings by remote experts, misfortune free and promptly accessible individual patient data, and enhanced correspondence between accomplices in a social insurance framework. The security of restorative data, in view of strict morals and authoritative tenets, offers rights to the in-patient and obligations to the experts. The necessity to secure medical images and other data on the in-patient is not just for privacy purposes but and to deter the manipulation that could occur by way of a malicious person throughout the transmission from medical center to another. If your medical image is tampered with and provided for a specialist or perhaps a radiologist, this may result in a wrong diagnosis that could cause severe problems or death. To supply the security to medical images, we present the comparative study of different swarm optimization algorithms. Based on the intelligence behavior we arrive at conclude that many of work could be in done in the foreseeable future for cat swarm optimization algorithm and hybrid swarm optimizations since these methods are best to supply the security for medical images such as for instance CT Images and DICOM images using Image Steganography.

Keywords*—CT Images; DICOM Images; Firefly; Cat Swarm; ACO; BFO; Lion Optimization; BFO*

I. INTRODUCTION

In the developing connected present day world, one may wish to have the capacity to ensure mystery of the correspondence as well as security of the communicators. Cloud correspondence enables one to convey without uncovering who is imparting. The Steganography, Cryptography and Digital Watermarking strategies can be utilized to acquire security and protection of information. The steganography is the specialty of concealing information inside information, for example, cover medium by applying diverse steganography strategies. While cryptography brings about making the information human mixed up shape called as figure along these lines cryptography is scrambling of messages. Though the steganography results in abuse of human mindfulness so it stays in secret and undetected or unblemished. It is conceivable to utilize all record medium, advanced information or documents as a cover medium in steganography. Swarm Intelligence is a piece of man-made consciousness. It dependent on the investigation of aggregate conduct in decentralized and self-sorted out systems [5]. The possibility of SI originates from frameworks found in nature, including subterranean insect states, fowl running and creature grouping that can be adequately connected to computationally insightful framework. Swarm Intelligence frameworks are normally comprised of a populace of operators collaborating locally with each other and with their condition and nearby associations between such hubs frequently lead to the rise of a worldwide behavior [6].

A. Swarm intelligence

Swarm knowledge is a rising field of organically motivated computerized reasoning dependent on the conduct models of social creepy crawlies, for example, ants, honey bees, wasps, termites and so forth. A Swarm is a design of a huge number of people that have picked their own will to join on a shared objective. Swarm Intelligence [8] is simply the Complex Collective, Organized, Coordinated, Flexible and Robust Behavior of a gathering following the straightforward guidelines. Swarm insight is a kind of multi-specialist framework whereby singular operators carry on as per straightforward standards however connect to create a shockingly proficient aggregate conduct. PSO is one type of swarm insight since every molecule flies through the hunt space by refreshing its individual speed at normal interims toward both the best position or area it by and by has found (i.e. the individual best), and toward the universally best position found by the whole swarm (i.e. the worldwide best). Since the capacity estimation of every molecule is iteratively or frequently assessed so as to figure out which offers the most reduced capacity esteem; and since that data influences the speed, and by suggestion the bearing, of each other molecule; a strikingly fit aggregate conduct develops.

B. Key Points of Swarm Intelligence

- One millions heads, one beautiful mind.
- Agents interactive locally with each other and the environment.
- Emergence of intelligent, Collective, Self-sorted out, Global conduct.
- Decentralized and fake or common.
- Very versatile.
- Applications of bio-inspired concepts.

- Randomness enables the continuous exploration of the alternatives and it ensures that the solutions will be found.

II. OBJECTIVE OF THE OPTIMIZATIONS

Optimization may be the quest for arrange of variables that either maximize or minimize a scalar cost function, f (x). The n-dimensional decision vector, x, consists of your n decision variables that the choice maker has control. The price tag function is multivariate as it determined by a few decision variable, as is usual of real-world relationships. The decision maker desires a much more efficient method than experience through which to getting a quality decision vector, in the future optimization techniques are employed [12]. When each decision variable is permitted to assume all real, integers, or other values making in the n-dimensional search space, the optimization is considered to be unconstrained. If you will discover further limitations at the allowable values of any decision variable, the optimization is considered to be constrained. Boundary constraints, which specify a maximum and/or minimum value for just about any or all decision variables, will not be necessarily considered to constitute constrained optimization, though this can literally be a case. If ever the Rocky Mountain Range, with its hills and valleys, represents an optimization function, with the purpose of the optimization problem being to search for the geographical coordinates that minimize the altitude of this function, the bottom of each valley and depression was obviously a local minimum in reference towards altitude that may be the fee function's value. The n-dimensional coordinates or decision vector the place an area minimum occurs is actually an area minimizer or local minimum point, deciding vector for being optimized features longitude during the horizontal dimension and latitude during the vertical dimension. For the reason that goal just for this example will be to find the lowest altitude of this mountain range, one might simply head inside a downward direction from current location, that lead him towards a local minimum; however, one would definitely not have a cause to trust that location to be a global minimum. Local optimization (LO) methods seek to buy a local minimum and, more importantly, its corresponding local minimizer, while global optimization (GO) methods attempt to search for the global minimum, or lowest function value, with its corresponding global minimizer.

III. SWARM INTELLIGENCE TECHNIQUES

Swarm intelligence [16] may be the discipline that handles natural and artificial systems made up of many individuals that coordinate using decentralized control and self-organization [2]. The key focus of swarm intelligence research is on the collective behavior that results from local interactions of people together and using their environment. It is a revolutionary technique for solving optimization problems that formerly took its inspiration from the biological examples that may be observed in nature, such as for example ant colonies, flocks of birds, fish schools and bee hives, where numerous people with limited capabilities are able to arrive at intelligent solutions for complex problems The social interactions among individual swarms could be either direct or indirect. The direct interaction is performed by audio or video. Examples are birds where they interact together through sound and bees interact through waggle dance. In the indirect interaction the agents talk with the surroundings i.e., one agent changes the surroundings and other agents react to the change. Example is ants where they communicate through the procedure called stigmergy in that the pheromone trail lay by the ants throughout the search of food [9]. Swarm intelligence is a relatively new subfield of artificial intelligence which studies the emergent collective intelligence of categories of simple agents. Computer researchers have tried to produce highly developed methods and systems that utilize the techniques of the swarms to locate methods to complex problems with assistance from their success and efficiency. SI systems are normally composed of a population of simple agents interacting locally with one another and using their environment. Swarm intelligence is becoming analysis interest a number of research scientists of connected fields in recent years [1]. The swarm intelligence is outlined as ‘‘any decide to create algorithms or distributed problem- resolution devices galvanized by the collective behaviour of social insect colonies and different animal societies."

The classical demonstration of a swarm is bees swarming around their hive; the same the style will undoubtedly be extended to different systems sticking with the same design. such as, associate hymenopter colony tend to be considered to be a swarm whose individual agents area unit associatets; a flock of birds may be a swarm of birds; an immune system is a swarm of cells additionally as viewers may be a swarm of persons [2].

A. Ant Colony Optimization

Ant colony optimization [2] is an approach for optimization that has been around since earlier 1990's. The inspiring way to obtain ant colony optimization could be the foraging behavior of real ant colonies. This behavior is exploited in artificial ant colonies for your search of approximate ways of discrete optimization problems, to continuous optimization problems, in order to important problems in telecommunications just like routing and load balancing. First, we take care of the biological inspiration of ant colony optimization algorithms. This algorithm is part of the ant colony algorithms family, in swarm intelligence methods, and it also constitutes some meta heuristic optimizations.

1) The principle contrasts between the conduct of the genuine ants and the conduct of the counterfeit ants in our model are as per the following:

- While real ant moves within their environment inside an asynchronous way, the artificial ants are synchronized, i.e. ateach iteration from the simulated system, each one of the artificial ants moves in the nest towards the meal source and follows the exact same path back.
- While real ants leave pheromone on the floor if he or she move, artificial [1] ants only deposit artificial pheromone enroute back towards nest.

- The foraging behavior of real ants is dependant on an implicit evaluation of an solution (i.e., a path through the nest to the food source). By implicit solution evaluation we mean the fact shorter paths will be completed earlier than longer ones, and as a consequence they will receive pheromone reinforcement more quickly. In contrast, the artificial antsevaluate an answer with regards to some quality measure used to ascertain the effectiveness of the pheromonere inforcement how the ants perform during their return visit to the nest.

B. Artificial bee colony

Artificial Bee Colony (ABC) is one of the most recently defined algorithms by Dervis Karabogain 2005, motivated by the intelligent behavior of honey bees. It is as simple as Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms, and uses only common control parameters such as colony size and maximum cycle number. ABC as an optimization tool, provides a population-based search procedure in which individuals called foods positions are modified by the artificial bees with time and the bee's aim is to discover the places of food sources with high nectar amount and finally the one with the highest nectar. In ABC system, artificial bees fly around in a multidimensional search space and some (employed and onlooker bees) choose food sources depending on the experience of themselves and their nest mates, and adjust their positions. Some (scouts) fly and choose the food sources randomly without using experience [13]. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus, ABC system combines local search methods, carried out by employed and onlooker bees, with global search methods, managed by onlookers and scouts, attempting to balance exploration and exploitation process.In ABC, the colony of artificial bees contains three groups of bees: employed bees associated with specific food sources, onlooker bees watching the dance of employed bees within the hive to choose a food source, and scout bees searching for food sources randomly. Both onlookers and scouts are also called unemployed bees.

Initially, all food source positions are discovered by scout bees. Thereafter, the nectar of food sources are exploited by employed bees and onlooker bees, and this continual exploitation will ultimately cause them to become exhausted. Then, the employed bee which was exploiting the exhausted food source becomes a scout bee in search of further food sources once again. In other words, the employed bee whose food source has been exhausted becomes a scout bee [14].

The general scheme of the ABC algorithm is as follows:

Initialization Phase

REPEAT

Employed Bees Phase

Onlooker Bees Phase

Scout Bees Phase

Memorize the best solution achieved so far

UNTIL(Cycle=Maximum Cycle Number or a Maximum CPU time)

C. PARTICLE SWARM OPTIMIZATION (PSO)

The basic PSO [11] model consists of a swarm of particles, which are initialized with a population of random candidate solutions. They move iteratively through the d-dimension problem space to search for the new solutions, where the fitness, f, can be calculated as the certain qualities measure[7]. Each particle has a position represented by a position-vector xi (i is the index of the particle), and a velocity represented by a velocity-vector vi. Each particle remembers its own best position so far in a vector i-th, and its d-dimensional value is pbest(pid).The best position-vector among the swarm so far is then stored in the vector i-th,and its d-th dimensional value is pbest(pgd). During the iteration time t, the update ofthe velocity (vid) from the previous velocity to the new velocity is determined by Eq.(1). The new position (xid) is then determined by the sum of the previous position and the new velocity by Eq. (2).

V(id+1) = w *vid + c1 *r1* (pgd -xid) +c2 * r2 * (pid -xid)… (1)

X(id+1) = xid + v(id+1)……..……………… (2)

where i =1,2,…..,N; w is the inertia weight, r1 and r2 are the random numbers, which are used to maintain the diversity of the population, and are uniformly distributed in the interval [0,1] for the d-th dimension of the i-th particle. c1 is a positive constant, called coefficient of the self recognition component; c2 is a positive constant, called coefficient of the social component. The general basic algorithm for the Particle Swarm Optimization can be described in algorithm (1) [8].

Input: Initialize the algorithm parameters (c1, c2, w, vmax, Swarm_Size, Max_Iter,r1,r2).

Output: The optimization having the highest fitness as found by PSO.

Step 1: Randomly generate the initial particles and velocities to form a swarm

Step 2: Calculate the fitness function of each of the particles.

Step 3: If the current position of the particle is better than the previous history, update the particles to indicate this fact.

Step 4: Find the best particle of the swarm. Update the positions of the particles by using equations (1) and (2).

Step 5: If the maximum number of iterations has exceeded or high fitness is found, then go to step 6 or else go to step 2.

Step 6: Copy the best value and exit.

Fig. 1: PSO Algorithm

D. LION OPTIMIZATION ALGORITHM (LOA)

Lions include the most socially inclined of wild cat species which display high levels of cooperation and antagonism. Unlike all your other cats, Lions typically hunt along with other members of their pride. Several lionesses work together and encircle the prey from different points and catch the victim with a fast attack. Coordinated group [15] hunting brings a much better possibility of success in lion hunts. The male lions and some lionesses usually stay and rest while awaiting the hunter lionesses to return on the hunt. Inside the work, some characters of lions are mathematically modeled in an effort to design an optimization algorithm. Within the proposed algorithm, Lion Optimization Algorithm (LOA), a primary human population is formed by some randomly generated solutions called Lions. A number of the lions in the initial population (%N) are selected as nomad lions and rest population(resident lions) is randomly partitioned into P subsets called prides. S percent in the pride's members are thought of as female and rest is thought of as male, even if this rate in nomad lions is or vice-versa [4].

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Lion Optimization Algorithm pseudo code

1. Generate random sample of Lions Npop(Npop is number of initial population).
2. Initiate prides and nomad lions

   i. Randomly select %N (Percent of lions that are nomad) of initial population as nomad lion. Partition remained lions into P (P is
      number of prides) prides randomly, and formed each pride's territory.
  ii. In each pride %S (Sex rate) of entire population are known as females and the rest as males. This rate in nomad lions is
      inversed.

3. For each pride do

   i. Some randomly selected female lion go hunting.
  ii. Each of remained female lion in pride go toward one of the best selected position from territory.
 iii. In pride, for each resident male; %R (Roaming percent) of territory randomly are selected and checked.
      %Ma (Mating probability) of females in pride mate with one or several resident male. → New cubs become mature.
  iv. Weakest male drive out from pride and become nomad.

4. For Nomad do

   i. Nomad lion (both male and female) moving randomly in search space.
      %Ma (Mating probability) of nomad Female mate with one of the best nomad male. → New cubs become mature.
  ii. Prides randomly attacked by nomad male.

5. For each pride do

   i. Some female with I rate ((Immigrate rate)) immigrate from pride and become nomad.

6. Do

   i. First, based on their fitness value each gender of the nomad lions are sorted. After that, the best females among them are
      selected and distributed to prides filling empty places of migrated females.
  ii. With respect to the maximum permitted number of each gender, nomad lions with the least fitness value will be removed.

If termination criterion is not satisfied, then go to step 3
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Fig. 2: Algorithmic steps for Lion Optimization Algorithm

E. BACTERIAL FORAGING OPTIMIZATION ALGORITHM (BFOA)

Bacterial Foraging Optimization Algorithm (BFOA) is proposed by Kevin Passino (2002), is a fresh comer to the household of nature inspired optimization algorithms. Putting on group foraging strategy of a swarm of E.coli bacteria in multi-optimal function optimization is the vital thing perception of this new algorithm. Bacteria try to find nutrients are a fashion to maximize energy obtained per unit time. Individual bacterium also communicates web-sites by sending signals [13]. A bacterium takes foraging decisions after considering two previous factors. Accomplishing this, when a bacterium moves by subtracting small steps while seeking nutrients, is named chemotactic. The true secret perception of BFOA is mimicking chemotactic movement of virtual bacteria inside problem search space.

p : Dimension of the search space,
S : Total amount of bacteria in the people,
Nc : The number of chemotactic steps,
Ns : The swimming length.
Nre : The number of reproduction steps,
Ned : The number of elimination-dispersal events,
Ped : Elimination-dispersal probability,
C(i): How big is the step taken in the random direction specified by the tumble.

Foraging theory is based on the assumption that animals look for and obtain nutrients in ways that maximizes their energy intake E per unit time T spent foraging. Hence, they fight to increase a function like E/T (or they maximize their long-term average rate of energy intake). Maximization of this kind of function provides nutrient sources to survive and additional time for other important activities (e.g., fighting, fleeing, mating, reproducing, sleeping, or shelter building).

F. FIREFLY ALGORITHM

The firefly algorithm is dependant on idealized behavior on the flashing characteristics of fireflies [9]. For simplicity, we could summarize these flashing characteristics as the following three rules: All fireflies are unisex, so any particular one firefly is attracted to other fireflies despite their sex. Attractiveness is proportional for their brightness, thus for virtually every two flashing fireflies, the less bright you will move to your brighter one. The attractiveness is proportional on the brightness and both decrease because their distance increases. If nobody is brighter than a selected firefly, it will eventually move randomly. The brightness of any firefly is affected or determined with the landscape of the aim function for being optimized [10]. Dependant on these three rules, the simple measures on the firefly algorithm (FA) could be summarized as shown in algorithm (2) [1].

```
Begin
    Initialize algorithm parameters:
        Max Gen: the maximal number of generations
        γ: the light absorption coefficient
        r: the particular distance from the light source
        d: the domain space
    Define the objective function of f(x), where x=(x1,........xd)^T
    Generate the initial population of fireflies or xi (i=1, 2 ,..., n)
    Determine the light intensity of Ii at xi via f(xi)
      While (t < Max Gen)
            For i = 1 to n (all n fireflies)
            For j=1 to n (n fireflies)
            if (Ij > Ii), move firefly i towards j; end if
    Attractiveness varies with distance r via Exp [-γ r^2]
    Evaluate new solutions and update light intensity;
            End for j
            End for i
    Rank the fireflies and find the current best;
    End while
      Post process results and Visualization
    End
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Fig. 3: Algorithmic steps for Firefly Optimization Algorithm.

G. CAT SWARM OPTIMIZATION

Cat Swarm Optimization (CSO) [6] is probably the new swarm intelligence algorithms for finding the best global solution. On account of complexity, sometimes the pure CSO takes a while to converge and cannot obtain the accurate solution. For solving this challenge and enhancing the convergence accuracy level, we propose a fresh improved CSO namely 'Adaptive Dynamic Cat Swarm Optimization '.Cat Swarm Optimization is a fresh optimization algorithm top swarm intelligence [4]. The CSO algorithm models the behavior of cats into two modes: 'Seeking mode 'and 'Tracing mode '. Swarm is made from initial population made up of particles to find in the most effective space. For instance, we can simulate birds, ants and bees and prepare Particle swarm optimization, Ant colony optimization and Bee colony optimization respectively. Here, in CSO, we use cats as particles for solving the problems.

In CSO, every cat features its own position made up of D dimensions, velocities for every dimension, a fitness value, which represents the accommodation of the kitten towards the fitness function, plus a flag to identify whether the kitten is in seeking mode or tracing mode. A final solution would be the best position of one of many cats. The CSO keeps the best solution until it reaches the end of the iterations [5].Cat Swarm Optimization algorithm has two modes to be able to solve problems which can be described below:

1) Seeking Mode:

For modeling [10] the behaviour of cats in resting a serious amounts of being-alert, we take advantage of the seeking mode. This mode is a time for thinking and deciding about next move. This mode has four main parameters which can be mentioned as follow: seeking memory pool (SMP), seeking range from the selected dimension (SRD), counts of dimension to modify (CDC) and self-position consideration (SPC) [4].

The process of seeking mode is describes as follow:

Step1: Make j copies of the prevailing position of catk, where j = SMP. If value of SPC is true, let j = (SMP-1), then keep the present position among the candidates.

Step2: For each copy, in line with CDC, randomly plus or minus SRD percent the prevailing values and replace the earlier ones.

Step3: Calculate the fitness values (FS) off candidate points.

Step4: If all FS are not quite equal, calculate the selecting probability of each candidate point by (1), otherwise set each of the selecting probability of each candidate point be 1.

Step5: Randomly pick the particular to shift to with the candidate points, and replace the task of catk.

$$P_i = \frac{|SSE_i - SSE_{max}|}{SSE_{max} - SSE_{min}}$$

If with regards to the fitness function is to find the minimum solution, FSb = FSmax, otherwise FSb = FSmin.

2) Tracing Mode:

Tracing mode will be the second mode of algorithm. During this mode, cats desire to follow targets and foods. Particles tracing mode is a follow:

Step1: Update the velocities for every single dimension according to (2).

Step2: Check if your velocities are in all the different maximum velocity. In case the new velocity is over-range, it is scheduled equal towards limit.

$$V_{k,d} = V_{k,d} + r_1 c_1 \left(X_{best,d} - X_{k,d}\right)$$

Step 3: Update the location of cat k

$$X_{k,d} = X_{k,d} + V_{k,d}$$

Xbest,d is the position of the kitten, who gets the best fitness value, Xk,d is the position of catk , c1 is undoubtedly an acceleration coefficient for extending the velocity of the kitten to move around in the answer space most likely equals 2.05 and r1 is often a random value uniformly generated in the plethora of [0,1].

The table I shows the comparative analysis of the different swarm optimization algorithms.

TABLE 1: Swarm Intelligence Algorithms

S. No.	Swarm Intelligence Algorithms		
	Name of Algorithm	Year of Development	Based on Technique
1	Altruism	Foster KR, Wenseleers T (2006)	Hamilton's rule of kin Selection
2	Ant Colony Optimization	Marco Dorgio (1992)	Ant
3	Artificial Bee Colony	Karaboga	Honey Bee
4	Artificial Immune System	De Castro & Von Zuben's (2002)	Abstract Structure and function of immune system
5	Particle Swarm Optimization	Kennedy &Eberhart (1995)	Inspired by Swarm
6	Charged System Search	Kaveh A. &Talatahari S. (2010)	Based on some principles from physics and mechanics
7	Cuckoo Search	Yang Xin- She & Deb Suash (2009)	Mimics the brooding behavior of some cuckoo species
8	Firefly Algorithm	Yang Xin- She (2008)	Inspired by the flashing behavior of fireflies.
9	Intelligent Water Drops	Shah-Hosseinihamed (2009)	Inspired by natural rivers and how they find almost optimal paths to their destination.
10	River formation Dynamics (RFD)	Gradient version of ACO	Based on copying how water forms rivers by eroding the ground and depositing sediments.
11	Gravitational Search Algorithm (GSA)	Rashedi, Nezamabadi pour &Saryazdi (2009)	Based on law of gravity and the notion of mass interaction.

IV. SELECTION OF SWARM OPTIMIZATION ALGORITHM FOR IMAGE STEGANOGRAPHY USING MEDICAL IMAGES

Function Optimization is just about the important fields inside computational intelligence theories. There are numerous algorithms to get the global and local solutions on the problems. Most of these optimization algorithms were developed determined by swarm intelligence. These algorithms imitate the creature's swarm behavior and model into algorithm, just like Ant Colony Optimization (ACO) which imitates the behaviour of ants [1]-[6], Particle Swarm Optimization (PSO) which imitates the behaviour of birds [2], Bee Colony Optimization (BCO) which imitates the behaviour of bees [3] and the current finding, Cat Swarm Optimization (CSO) which imitates the behaviour of cats [4]. By simulating the behaviour of cats and modeling into two modes, CSO can solve the optimization problems. In the cases of functions optimization, CSO is one of the better algorithms to get the global solution. As compared to other heuristic algorithms just like PSO and PSO with weighting factor [7], CSO usually achieves better result. But, as a result of algorithm complexity, solving the down sides and finding the perfect solution usually takes a protracted process some time to sometimes much iteration is needed. So based on the study, we can conclude that, few swarm optimization techniques were already been used for image Steganography such as Genetic, ACO, PSO and firefly and BFO etc. But there is a lot of work can be done using swarm optimization algorithms for image Steganography for medical images such as CT and DICOM images. The latest Cat swarm optimization algorithm is best suited for the image Steganography. We can also use the hybrid optimization techniques for image Steganography.

V. CONCLUSION

Steganography is one type of security in the Internet world. However, steganography methods have the disadvantage that when their method is known, the embedded message could be deduced. Therefore, different techniques are developed in order to strengthening steganographic algorithms, such as for example swarm intelligence. This paper presents the research of different swarm optimization techniques such as for example ACO, PSO, Bee Optimization, BFO, firefly and Cat Swarm Optimization (CSO) algorithms for finding best positions inside image cover in order to embed text message. Based on the swarm behavior of different optimization algorithms, we come to conclude that, cat swarm optimization and hybrid way of swarm optimizations can be utilized for image Steganography in future.

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