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USE OF PARTICLE SWARM OPTIMIZATION IN HYBRID INTELLIGENT SYSTEMS

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Abstract- Particle swarm optimization (PSO) is based upon the concept of Swarm Intelligence and has emerged as a widely used optimization method. It has become a very interesting topic for research on account of its simplicity and efficiency. The standard PSO suffers from two main disadvantages of premature convergence and getting stuck at local maxima. So far many hybrid forms of PSO method have been developed and used in many applications to make it more effective. The following is a review paper providing an intensive survey of the various hybrid PSO algorithms developed and how they have been able to overcome the deficiencies in the standard PSO algorithm.
Keywords- Swarm Intelligence, Particle Swarm Optimization, convergence speed, efficiency, hybrid methods, applications.

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Introduction

PSO is a population based stochastic search method which was first introduced by Kennedy and Eberhart [1] in 1995 and has ever since been widely used to solve optimization problems. In order to overcome the problems in the standard PSO method many hybrid algorithms with PSO technique have been developed so far to make it more efficient and versatile.

Particle Swarm Optimization

PSO is an evolutionary computation technique that has been modelled on the biological behaviour of *swarms* such as bird flocking and fish schooling. A swarm refers to a collection of a number of potential solutions where each potential solution is known as a 'particle'. In the standard PSO method, each particle is initialized with random positions X_i and velocities V_i, and a function f (*fitness function*) is evaluated. The aim of PSO algorithm is to find the particle's position that gives the best evaluation of a given fitness function by using the particle's positional coordinates as input values. In a k-dimensional search space, $X_i = (x_i1, x_i2, x_i3,..., x_ik)$ and $V_i = (v_i1, v_i2, v_i3,...,v_ik)$. Positions and velocities are adjusted and the function is evaluated with the new coordinates at each step. In each generation every particle updates itself continuously by following two extreme values; the best position of the particle in its neighbourhood (known as *local best* or *personal best* position) and the best position in the *swarm* at that time (known as *global best* position) [2]. After finding the above values each particle updates its position and velocity as follows:

$$v_{i.k}(t+1) = wv_{i.k}(t) + c_1r_{1.k}(t)\,(y_{i.k}(t) - x_{i.k}(t)) + c_2r_{2.k}(t)\,(y`_k(t) - x_{i.k}(t)) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (2)$$

Where:

$v_{i.k}$ is the velocity of the *i-th* particle in the *t-th* iteration of the *k-th* dimension, $x_{i.k}$ is the position of the *i-th* particle in the *t-th* iteration of the *k-th* dimension, r_I and r_2 are random numbers in the interval [0, 1], c_I and c_2 are learning factors, in general $c_1=c_2=2$, '*w*' is the *inertia weight* factor selected in the range (0.1, 0. 9). This parameter was introduced in [3] which illustrated its significance in the particle swarm optimizer. Another improvement in the original version other than the introduction of inertia weight factor was the introduction of the *constriction factor* [4] that too resulted in fast convergence of the PSO algorithm. In equation (1) of the original version of PSO $v_{i.k}$ is limited to the range ($-V_{max}$, $+V_{max}$) where V_{max} parameter was introduced to limit the step size or the velocity to prevent the explosion that results due to the random weighting of the control parameters in the algorithm. Coefficients can be applied to various parts of the formula in order to guarantee convergence, while encouraging exploration.

Equation (1) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience and the group's best experience. The velocity is thus calculated based on three contributions:

a. A fraction of the previous velocity.
b. The *cognitive* component which is a function of the distance of the particle from its personal best position.
c. The *social* component which is a function of the distance of the particle from the best particle found thus far (i.e. the best of the personal bests).

The particle flies towards a new position according to equation (2). The PSO is usually executed with repeated application of equations (1) and (2) until a specified number of iterations have been exceeded or when the velocity updates are close to zero over a number of iterations.

Problems in standard PSO algorithm

There are many issues concerning the efficiency of standard PSO method such as selection of intelligent parameters, convergence speed, accuracy and provision of a global best solution rather than sticking to local optima. Some of these issues have been considered and dealt with by incorporating hybrid approaches based on PSO method.

Survey of Hybrid Techniques

Hybridization is a technique where we combine two or more algorithms/techniques in a judicious manner such that the resulting algorithm contains the positive features of all the combined algorithms [5]. Many hybrids of PSO have been developed so far so as to harness the strong points of the PSO algorithm and further improve its efficiency and accuracy with the hybridizing algorithms.

Hybrid K-means and PSO

The earliest hybrid method developed was by combining standard PSO with K-means method. The K-means algorithm tends to converge faster (after less function evaluations) than the PSO, but usually with a less accurate clustering, therefore a hybrid form of PSO and K-means is developed with a purpose to exploit the strong points of both these algorithms. This hybrid approach [2] has been followed to improve the efficiency of PSO in clustering analysis with K-means algorithm. This algorithm combines the ability of globalised searching of PSO and fast convergence of K-means. This was done by using the result of K-means as an initial seed to the swarm before applying PSO algorithm. As compared to the standard PSO algorithm the hybrid approach resulted into better convergence to lower quantization errors, larger inter-cluster distances and smaller intra-cluster distances. An effective PSO data clustering has been demonstrated in [6]. It has also been employed in [7] for the purpose of fast and high-quality document clustering to effectively navigate, summarize and organise information. In [8] C.M Cohen and Castro have employed PSO for data clustering by adapting this algorithm to position prototypes (particles) in regions of the space that represent natural clusters of the input data set.

Artificial Neural Network and PSO

In [9] QSAR (Quantitative Structure-Activity Relationships) models were built using a hybrid approach with artificial neural networks and PSO. It compares an earlier approach that used BPSO-BP (hybrid of *Binary PSO* and *Back –Propagation networks*) method to a newly proposed approach that uses *BPSO-PSO*. The earlier approach used Binary Particle Swarm Optimization (BPSO) for feature selection in its first stage, and a back propagation neural network in its second stage to provide a QSAR model based on the features selected in the first stage. In BPSO, unlike standard PSO, which takes real valued dimensions, there are only two possible discrete values (0 or 1) for each dimension of a particle. The author has proposed a re-established method of the previous one by using PSO in the second stage that results into robust QSAR models and reduces the variability due to the choice of back propagation parameters. A hybrid approach using neural networks and PSO has been applied in [10] to forecast daily peak loads e.g. Short term load forecasting (STLF) which plays a significant role in national as well as regional power planning and operation with insufficient electric energy increased need.

PSO with Simulated Annealing

In [11] the concept of simulated annealing (SA) was introduced into PSO which was known as PSO with Simulated Annealing (PSOwSA). In PSOwSA, the particle x_i won't move to the next position x'_i directly if the next position is worse than the current position. It just moves with probability P_T,

$$P_T = e^{(-(f(x'_i) - f(x_i))/T)} \qquad (4)$$

Where:

f is estimate function and probability P_T can be controlled by the temperature T. The particle can't easily escape out of the hopeful searching area and "local search" ability of the particle will be enforced if the temperature T falls slowly enough. Although PSOwSA works better than PSO in terms of improving the searching ability of particles in normal optimization problems but in dynamic environments both algorithms work equally. With respect to discrete optimization problems an improved Binary PSO proposed in [12] and in comparison to three algorithms viz. traditional BPSO, Binary Simulated Annealing Particle Swarm Optimization Algorithm (BSAPSO) and Binary Cross Particle Swarm Optimization Algorithm (BCPSO), the hybrid algorithm is better in terms of convergence speed, global optimization capacity and stability.

Rough Set Theory and PSO

The rough set theory emerged as a promising mathematical tool for extracting knowledge from datasets that contain noise as an imperfection, or unknown values and errors due to inaccurate measuring equipment. In [13] a hybrid rough-PSO technique has been used for the purpose of grouping the pixels of an image such as medical or remote satellite images that are often corrupted with noise. The challenging problem of image segmentation has been treated as a clustering problem using a hybrid approach of rough set theory and PSO technique.

PSO with GA (Genetic Algorithm)

The efficiency of the hybrid PSO-K means clustering algorithm in [2] has been improved by proposing a hybrid two phase GAI-PSO+K means algorithm [14]. It is a genetically improved version of PSO in which during the first phase we utilize the new genetically improved particle swarm optimization algorithm (GAI-PSO), a population based heuristic search technique modelled on the hybrid of cultural and social rules derived from the analysis of the swarm intelligence (PSO) and the concepts of natural selection and evolution (GA). The GAI-PSO combines the standard velocity and position update rules of PSO with the ideas of selection, mutation and crossover operations from GA. The GAI-PSO algorithm searches the solution space to find the optimal initial cluster centroids for the next phase. In the second phase a local refining stage utilizing the K-means algorithm takes place which efficiently converges to the optimal solution. This proposed method outperforms many previous approaches such as SA, PSO, and K-means with respect to numerous partitioning clustering problems. A hybrid of genetic algorithm and particle swarm optimization algorithm has been applied for order clustering in [15] and the result achieved was an improved production performance by effectively reducing the production time and machine idle time.

Quantum PSO

The Quantum Particle Swarm Optimization (QPSO) algorithm [16] [17] not only inherits the advantages of PSO algorithm, but also has further improvements. A modified quantum behaved particle swarm optimization [18] proposed for constrained optimization was introduced with double fitness values defined for every particle. Whether the particle is better or not will be decided by its two fitness values. QPSO has superior search performance than PSO and has strong global search ability and high efficiency. QPSO has been applied in many areas such as image colour segmentation [19], training network traffic prediction based on Back Propagation Neural Network [20], and solving mixed integer nonlinear programming [21]. A hybrid algorithm combining QPSO and K-medoids which is named as QKSCO [22] was designed for spatial clustering with obstacles constraints to exploit QPSO's rapid global convergence to separate the global clusters first and then find the optimal exact solutions of clusters by K-medoids method applied specifically to spatial clustering. A diversity-guided quantum behaved particle swarm optimization algorithm [23] based on clustering coefficient and characteristic distance has better optimization performance than other algorithms and overcomes the drawback of premature convergence caused by the loss of population diversity.

Some Recent Developments in PSO

An intelligent method using another particle swarm optimization algorithm [24] has been used to optimize the procedure of parameter selection. The parameters selected by this method are better than the experience parameters in terms of optimal fitness, mean of optimal fitness and convergence rate. A new hybrid optimization method [25] combines the best features of four traditional optimization methods together with an intelligent adjustment algorithm to speed convergence on unconstrained and constrained optimization problems. It provides a comprehensive sensitivity analysis of the traditional optimization methods within the hybrid group and is used to demonstrate how the relationship among the design variables in a given problem can be used to adjust algorithm parameters. Particle swarm optimization with iterative improvement strategy [26] is better than particle swarm optimization without iterative improvement strategy on the performance with the same conditions. As far as the high dimensional problems are concerned the standard PSO suffers from premature convergence. To remedy this fault an algorithm which combines the canonical PSO with a Chaotic and Gaussian local search procedure known as (CGPSO)[27] explores a wide search space that helps avoid premature convergence through Chaotic local search. In a novel variant of PSO called Cellular Particle Swarm Optimization (CPSO) [28] the authors have explored how Particle Swarm Optimization technique works in the view of Cellular Automata (CA) by providing a mechanism whereby CA is integrated in the velocity update to modify the trajectories of particles to avoid being trapped in local optimum.

Conclusion

Particle Swarm Optimization method based upon the concept of Swarm Intelligence is an extremely efficient optimization algorithm that is currently being used in numerous applications such as high-dimensional clustering analysis, web usage mining, image segmentation, wireless sensor networks, stock-market prediction etc. In the past few years many hybrid algorithms with PSO technique have emerged and there is still a lot of future scope and enhancements being brought about to further improve its efficiency and scope. The recent developments show that hybrid PSO methods are an interesting area to attract many other researchers and will emerge as a successful optimization technique in diverse applications.

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