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Improved Centripetal Accelerated Particle Swarm Optimization for Relevance Feedback in Medical Image Retrieval

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Abstract

Centripetal Accelerated Particle Swarm Optimization (CAPSO) is a recent and well embraced, interest stimulating topic in swarm intelligence (SI). The original CAPSO method does not have parameters to tune or adjust, so two new parameters are introduced to catapult the efficiency and boost the overall performance. For further enhancement of the algorithm's efficiency, the principle of quantum-behaved particles is also added. In evaluating the capability of the Improved Centripetal Accelerated Particle Swarm Optimization (ICAPSO) algorithm, we tested it on medical image database, in the aspect of Relevance Feedback of a Content-Based Image Retrieval (CBIR) system, clearly, ICAPSO outperformed others.

Keywords*: Particle swarm optimization; centripetal acceleration; quantum particle; relevance feedback; angle of rotation, radius of rotation*

1. Introduction

The importance of mimicking natural systems in science cannot be over emphasized as the benefits are evident in our today's scientific community. One of such applications is the imitation of animal behaviour called, Particle Swarm Optimization (PSO). It is an evolutionary computation technique which Dr. Eberhart and Dr. Kennedy introduced in 1995, basically inspired by social behaviour of bees, ants, fish schooling (shoaling), bird flocking *etc*. In it, optimal solution is achieved by the exchange of information among particles; each particle is a potential solution [1]. Swarm intelligence (SI) techniques are applied in diverse problems, especially, in data mining, neural networks training, optimal design of experiments, signal processing [2], *etc*. There are many SI algorithms developed in recent times such as, artificial immune system (AIS), gravitational search algorithm (GSA), Ant colony optimization (ACO), artificial bee colony (ABC) *etc*.[3][4][5][6].These algorithms are composed of simple particles or agents that interact locally with one another and with their environment to yield the desired output of a search task [7].

Here, the particles of PSO constitute the swarm, initialized with a population of random solutions. The search aims at the optima in accordance with a fitness function of each particle by updating the particles over generations [8]. Although, there are numerous algorithms developed, PSO has gained so much recognition due to its relative efficiency, in addition to implementation simplicity [9]. It is known that most existing SI algorithms such as greedy search algorithms suffer from different setbacks, like stagnation in local optima, as such, PSO is needed in overcoming these bottlenecks [10]. In 1997, Kennedy proposed the binary version of PSO (BPSO), which has been improved upon by Jun Sun *et al*, they proposed the quantum version of binary PSO (BQPSO) in 2007 [11][12][13]. And in 2013, Zahra Beheshti, *et al*, proposed Centripetal Accelerated Particle Swarm Optimization (CAPSO) [14], CAPSO was stated to accelerate the learning and

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convergence of optimization problems, this work by Zahra Beheshti, *et al*, has actually opened up many insights for further improvements.

The CAPSO method is a very inspiring development but as we know there is no super single existing method that is possible to solve all optimization problems completely, CAPSO also has its limitations. Hence, it is appropriate to make greater improvements on CAPSO to curb the problems of; (a) adjustable parameters, (b) local optima trapping, (c) stagnation, (d) randomness regulation, (e) slow performance, (f) inconsistency, (g) premature convergence, and (h) the problems of binary and real valued solutions. The CAPSO method does not have parameters to tune or adjust, so the parameters introduced in this paper will catapult the efficiency and further boost the overall performance. These two parameters are;

(a) Angle of rotation $\boldsymbol{\theta}$, of the individual particles in the search space.

(b) Radius of rotation $\boldsymbol{r}$, of the individual particles in the search space.

These adjustable parameters are evidently important in the individual particle's movement in the search space. Furthermore, the quantum-behaved particles idea introduced gives it the relative ease to evaluate the relevant particles during exploitation of the solution space.

The capability of ICAPSO was tested on an image database in Relevance feedback application of a Content-Based Image Retrieval (CBIR) system. A CBIR system retrieves images from a database that should be semantically relevant and similar to a query image while relevance feedback (RF) automatically fine-tunes a query using the input information to retrieve images [15]. During image query, RF is useful as there are semantic gaps between the query image and the output by evaluating the feedback image [16].

2. Improved Centripetal–Accelerated Particles Swarm Optimization (ICAPSO)

2.1. Adding Two Factors to CAPSO

In PSO, we assume a global optimization algorithm in which every practical and possible solution is represented as a point or surface in a multi-dimensional feature space. All particles move with an attraction towards the best solution which every individual has located within its neighbourhood. That neighbourhood is the area described for each individual particle as the subset of particles for which communication is possible [17].

A given particle *i*, composed of three vectors, distance, positions and velocity;

(a) Its position in the D-dimensional search space; $\vec{x}_i = (x_{i1}, x_{i2}, \cdots x_{id})$,

(b) Individual best position found; $\vec{P}_i = (P_{i1}, P_{i2}, \cdots P_{id})$

(c) Its velocity; $\vec{v}_i = (v_{i1}, v_{i2}, \cdots v_{id})$, in each case *i*= 1,2,…,n.

All particles move throughout the search space by equations of update for each particle's movement. Given $\vec{p}_i$ and $\vec{p}_g$, the next velocity and position in the direction $\boldsymbol{d}$, are updated as;

$$v_i(t+1) = w(t) \times v_i(t) + c_1 \times rand \times (P_i(t) - x_i(t)) + c_2 \times rand \times (P_g(t) - x_i(t)) \quad (1)$$

and

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

Where, $v_i(t)$ and $v_i(t+1)$ are respectively, the present and next velocity of the *i*th particle, *w* is the inertial weight, c_1 and c_2 are constants of acceleration, ***rand*** represents uniformly random number within [0, 1], then $x_i(t)$ and $x_i(t+1)$ are the present and next positions.

The acceleration of the particle i, with respect to the force and mass acting on it, is;

$$a_i(t) = \frac{F_i(t)}{M_i(t)} \tag{3}$$

The velocity is as in eq.(4) and the position is as in eq.(2) respectively;

$$v_i(t+1) = v_i(t) + rand \times a_i(t) \tag{4}$$

Centripetal-accelerated particle swarm optimization (CAPSO) has been adopted as a result of the laws of motion combined with the PSO algorithm applied in a search space.

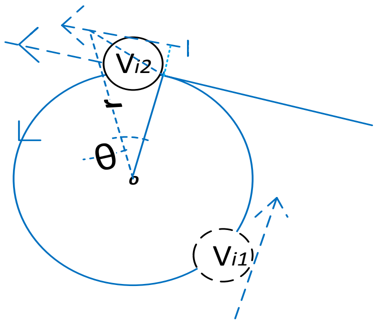

Figure 1. An Agent *I*, Under the Influence of Centripetal Acceleration

Figure 1, shows an agent ***i***, changing direction which results to acceleration, the radius ***r*** and the angle ***θ*** influence the movement of the particle with reduced radius, its centripetal acceleration increases and vice versa.

A change in time Δt, the initial velocity of an agent i is $v_i(t)$, as it moves from position $x_i(t)$ to a new position $x_i(t+1)$, the new velocity is $v_i(t+1)$, then the object's acceleration is;

$$a_i = \frac{v_i(t+1) - v_i(t)}{\Delta t} \tag{5}$$

The new velocity $v_i(t+1)$ is gotten from eq. (5); $v_i(t+1) = v_i(t) + a\Delta t$ (6)

and the distance travelled is;

$$x_i(t+1) = x_i(t) + \frac{1}{2}a\Delta t^2 + v_i(t)\Delta t \tag{7}$$

The idea of CAPSO also employs the laws of motion in mechanics and the PSO algorithm. In this algorithm, an ith particle or agent is defined with four attributes: position, velocity, acceleration and centripetal acceleration, in a d-dimensional search space. It is worthwhile to state that, $\vec{p}_g$ is selected based on *gbest* and *lbest* processes and the particles update the velocity based on the current values of velocity, acceleration and centripetal acceleration as in the following;

$$v_i(t+1) = v_i(t) + a_i(t) + A_i(t) \tag{8}$$

Where $v_i(t)$ and $v_i(t+1)$ denote present and the next possible velocity, $a_i(t)$ is the acceleration, defined as;

$$a_i(t) = rand \times (P_i(t) - x_i(t)) + rand \times (P_g(t) - x_i(t)) \tag{9}$$

where ***rand*** is a random number with uniform distribution in the interval, [0,1], $x_i(t)$ is the current position, $P_i(t)$ is the personal best position of the ith particle and $P_g(t)$ is the global best position explored so far by the population. The centripetal acceleration $A_i(t)$ is given as;

$$A_i(t) = E_i(t) \times rand \times [P_i(t) - (P_{med}(t) + x_i(t))] \tag{10}$$

where $P_{med}(t)$ is the current median position of the particles in *d*-dimensional space and $E_i(t)$ is the coefficient of acceleration, defined as; $e_i(t) = fit_i(t) - GW_{fit}(t)$ and

$$E_i(t) = \frac{e_i(t)}{\sum_{j=1}^{n} e_j(t)} \tag{11}$$

where $i = 1,2,\cdots,n$, $fit_i(t)$ is the fitness value of the particle *i* and $GW_{fit}(t)$ is the explored worst fitness value so far by the swarm. The movement of the agents is influenced by vertical and horizontal forces with the attributes of; (a) Velocity ***v***, (b) Mass ***m*** (inertia/ tension), (c) Radius of rotation ***r***, and (d) Angle of rotation ***θ***. From equation (8), $A_i(t)$ is the centripetal acceleration, so we equate it to gravitational force component, horizontal and vertical forces to enable us deduce the adjustable parameters of angle of rotation ***θ*** and radius of rotation ***r*.** Hence, ICAPSO algorithm can be fine-tuned and well controlled which is not possible in the CAPSO method. The centripetal acceleration (force) $A_i(t)$ here is as a result of the effect of the forces mentioned above;

$$\sum A_i(t) = m\frac{v^2}{r} = G\frac{m_1 m_2}{r^2} \quad \text{(Gravitational force components)} \tag{12}$$

$$\sum A_i(t) = T_i \sin\theta = m\frac{v^2}{r} \quad \text{(Horizontal components)} \tag{13}$$

$$\sum A_i(t) = T_i \cos\theta = mg \quad \text{(Vertical components)} \tag{14}$$

Equating all equations, then divide (13) by (14),

$\frac{\sin\theta}{\cos\theta} = \frac{v^2}{rg}$, this implies that; $\tan\theta = \frac{v^2}{rg}$ hence, $\theta = \tan^{-1}[v^2(rg)^{-1}]$.

The current angle ***θ*** of the particle ***i***, is of its new velocity, radius of rotation ***r*** and time ***t***;

$$\theta = \tan^{-1}[(v_i(t+1))^2(rg)^{-1}] \text{ where ; } r \neq 0 \tag{15}$$

where T_i is the tension due to the inertia possessed by the particle *i*, *v* is the velocity of the particle, ***r*** is an adjustable radius of rotation within the solution space and ***r*** ≠ 0, ***g*** is the acceleration due to gravity and ***θ*** is angle of rotation. For every centripetal-accelerated particle *i*, from the right hand sides (R.H.S) of equations (13) and (14), we can substitute for the value of $A_i(t)$ (centripetal Acceleration) in equation (8) to regulate the algorithm. Then utilising equation (15), we can obtain the relevant values of ***θ*** with some arbitrary values of ***r***.

Another valuable improvement of CAPSO is the introduction of the principle of quantum behaved particles in the algorithm, here, a chosen particle will be assigned the quantity 1 and the particle neglected will have the value 0. Furthermore, by adopting a quantum rotation gate, particles can be in any linear superposition state of 0 and 1. The significant improvements are:

1. Agents trapped/ stagnated in local optimum escape rapidly.
2. Angle ***θ*** and radius of rotation ***r*,** ensure optimal solution, as the exploration and exploitation time become minimal due to the varied centripetal acceleration.
3. Only agents with high centripetal acceleration are dimmed fit.

The value of ***θ*** regulates the trapped agents' escape velocity in local optimum, in the same vein, the change of the values of ***r***, changes the particles' acceleration. To avoid premature exploitation in the solution space, the values of ***θ*** and ***r***, are then gradually adjusted.

2.2. Quantum Influence on Centripetal–Accelerated Particles

The idea of Quantum inspired Particle Swarm Optimization is a new optimization method stemmed from quantum mechanics. In ICAPSO, the application of quantum principle is that, the particle which conveys information is referred to as a *Q*-bit. A quantum particle vector can be defined as; $Q(t)=[q^1(t),q^2(t),\ldots q^n(t)]\times\{q^j(t)=[q_1^j(t),q_2^j(t),\ldots q_m^j(t)]\}$

where, $0 \le q_{i1}^j(t) \le 1,(i=1,2,\ldots m, and, j=1,2\ldots n)$, *m*, being the particle's length, *n* the size of the population, $q_i^j(t)$ the probability of the *i*th bit of the *j*th particle to have the value 0 in the *i*th iteration or generation. It is a two state system as the *Q*-bit with two directions through polarization and can be denoted by two complex number values of α and β showing the amplitude of the probability of the two quantum states of "0" and "1".

The usual form of the *Q*-bit individuals 0 and 1 values are written as; $|\Psi\rangle\alpha|0\rangle+\beta|1\rangle$, $|0\rangle$ and $|1\rangle$ respectively represent the *Q*-bit values 0 and 1. In the ICAPSO model, to update the particles' positions, the quantum angular value θ is important. The *Q*-bit values satisfy, $|\sin(\theta)|^2+|\cos(\theta)|^2=1$, with regards to the angular velocity θ, the new probability of α and β are calculated using the rotation gate as;

$$\begin{bmatrix}\alpha\\ \beta\end{bmatrix}=\begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta)\\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix}\begin{bmatrix}\alpha_{t-1}\\ \beta_{t-1}\end{bmatrix} \tag{16}$$

The fundamental equation to update the velocity in conventional PSO is adjusted to give a simplified quantum angle then expressed as the new value of the *Q*-bit as;

$$\Delta\theta(t+1)=w(t)\times\Delta\theta(t)+c_1\times rand\times(\theta_{gbest}(t)-\theta(t))+c_2\times rand\times(\theta_{pbest}(t)-\theta(t)) \tag{17}$$

where, w, c_1 and c_2 are as in eq.(1).

2.3. The ICAPSO Algorithm

The process starts by initializing the population size, position, dimension of all particles and particle's fitness (see Figure 2).

i. Compute the mean best position of the population.
ii. Update each agent's best position and the global best position.
iii. Compute the neighbourhood attraction in every locality.
iv. Update the position & experience of agents, then exchange information.
v. Increase the centripetal acceleration in local extrema.
vi. Update the agents' positions, angle of rotation $\boldsymbol{\theta}$, and radius of rotation $\boldsymbol{r}$, compute the global best position and share the information among agents.
vii. Identify relevant agents in the solution space and compute the best global position.
viii. Continue the process until the maximum iteration is reached.

A quantum algorithm of such, computes almost all values at the same time. It is this exponential growth of the state space with the number of particles that suggests exponential speed-up of computation in quantum algorithm combined with the centripetal acceleration which propel the particles trapped in a local optimum. Every quantum operation handles all other states available in the superposition state in parallel.

Given an objective function $f(x)=f(x_1,x_2,\ldots x_n)$, in the solution space, some solution vectors drift toward the global optimum while some away from the global optimum**.** A condition where the value of the present objective function is poorer than its past value, our ICAPSO shifts the solution vectors quickly to new positions with the enhanced centripetal-acceleration on the quantum-behaved particles. All particles retain the former value until a better value is obtained, then, with better objective function value, *pbest* and *gbest* are updated and all information about its previous experience is forgone.

3. ICAPSO Application for Relevance Feedback (RF) In Medical Image Retrieval

In retrieving relevant contents of an image such as; shape, texture, colour and spatial layout the image contents are rigorously evaluated. Although the task is daunting therefore this multi-routing method yields a more efficient way in solving these problems, it clearly reduces multiple iteration and saves time. The digital image is converted to feature vector, likewise, all images in the database will form a feature database.

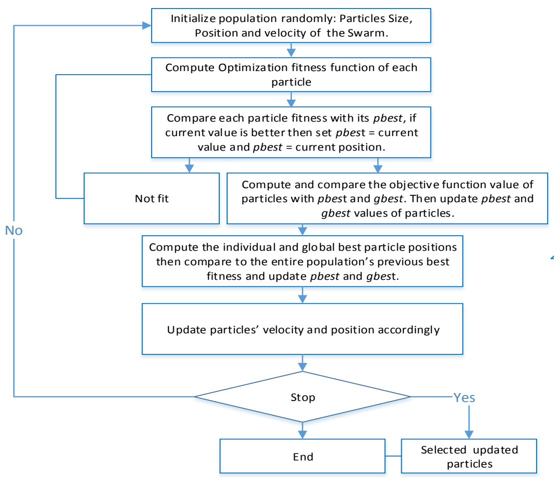

Figure 2. Flowchart of ICAPSO Algorithm

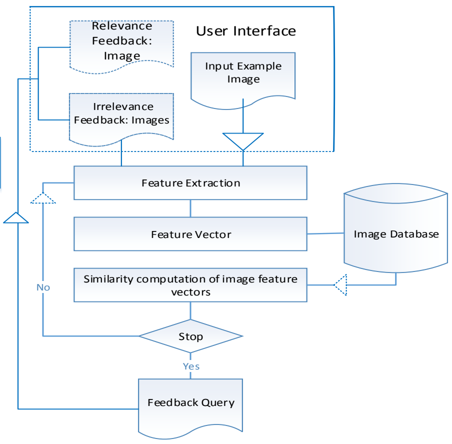

Figure 3. Relevance Feedback Process

Relevance Feedback (RF) process requires the altering of the query with the available query information feedback for the user to ascertain whether or not a retrieved object is relevant.

4. Experiments

To ascertain the robustness of the algorithm, an experiment was carried out using the Brain-Web simulated MR database images (http://www.bic.mni.mcgill.ca/brainweb), run on a 32-bit windows 7 operating system, processor: Intel®, core™, Duo 3.00GHz, RAM: 4GB computer, implemented with MATLAB R2012a. There were three (3) groups of the images; X (167 images), Y (217 images) and Z (180 images), a total of 564 images, made up of the brain images slices with different shapes and features.

In the experiment, 80 images were randomly picked out from each group summing up to 240 images, in which four (4) iterations were carried out. Basic image descriptor sets were adopted to focus on low-level visual features. Figure 5 below, was the query image, our algorithm was aimed to yield relevance feedback from the image database. Exactly similar images to the query image and other quite similar images are considered as the relevance feedback, ranked accordingly. Three other methods; Particle swarm optimization (PSO), Binary particles swarm optimization (BPSO) and Centripetal-accelerated particles swarm optimization (CAPSO), were compared with the ICAPSO–RF method. It was observed that ICAPSO–RF performed better in the application than the other three (3) methods. The only setback was on the 3rd iteration when the angle $\boldsymbol{\theta}$**,** was made larger than it was in other iterations, the performance of ICAPSO–RF was about 3.7% less than CAPSO in the 3rd iteration otherwise, our ICAPSO–RF out performed all the other methods (PSO, BPSO and CAPSO). The query was performed with reference to the example image, after the four iterations all relevantly retrieved images were added to a class of relevance feedback (RF; Positive Feedback), then those set of irrelevant images were grouped as the class of irrelevance feedback (Negative Feedback).

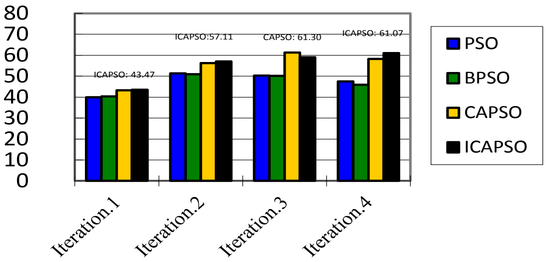

Figure 4.Relevance Feedback Comparison of PSO, BPSO, CAPSO and ICAPSO

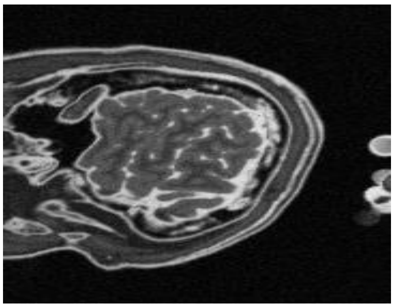

Figure 5. An Example Image

Figure 4 shows a performance of all the four methods, it indicates that ICAPSO has the best output while Figure 5 on the right (RHS) is the query image in the experiment.

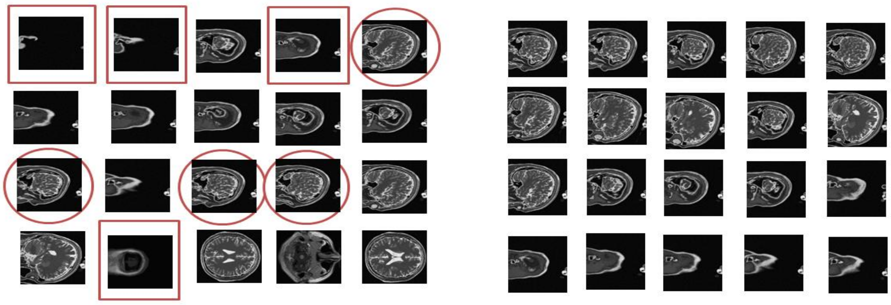

Figure6. Initial Feedback (Left) and Final Relevance Feedback (Right)

In Figure 6, on the left is an initial feedback, the images marked in red rectangles are irrelevant while on the right is the final feedback images ordered by relevancy.

5. Conclusion

The experiment of this paper was aimed at showing the efficiency of ICAPSO to locate relevant images from a dataset. In this case, the Brain-Web MR image database was used to test and classify the relevant images as relevance feedback. It was clearly observed that by varying the angle of rotation θ and radius of rotation $\boldsymbol{r}$, a great change in the performance of the system was affected in terms of speed and accuracy in the process. Furthermore, when the radius of rotation was gradually altered, the stagnation was reduced and randomness of the particles increased, all of these parameters had significant influence in the improvement of the algorithm. It is worth to mention that our method is more robust and efficient than the other PSO based methods, which is a valuable achievement, avoids multi-iteration and saves time.

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