Quantum Potential Swarm Optimization of PD Controller for Cargo Ship Steering

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Abstract: - This paper delineates the first attempt to combine the ideas from Centroidal Voronoi Tessellation (CVT), Quantum-Oscillator based Particle Swarm Optimization (QOPSO) and Quantum Clustering (QC) to realize a novel optimization approach named as Quantum Potential Swarm Optimization (QPOSO) based on quantum mechanics principle. The particles in standard PSO move along a determined trajectory in Newtonian mechanics, but in QPOS, the particles will exhibit quantum behaviour and bound to work in different principle. In addition, Centroidal Voronoi Tessellation (CVT) is implemented to distribute numerous quantum particles uniformly to ensure full coverage of search space. Quantum potential wells can be induced from the solutions given by quantum particles using quantum clustering technique. The strategic starting positions of quantum particle are then selected based on the minimal of quantum potential wells. The implementation of QPOSO to optimize a PD-type autopilot for a cargo ship is presented. The tuning of the PD controller parameters are considered to be difficult and tedious due to the high nonlinearity of the ship dynamic model and the external disturbances. However, QPOSO can provide a very promising technique for its simplicity and ease of use. The promising results from the experiment provide direct evidence for the feasibility and effectiveness of QPOSO for autopilot control of cargo ship.

Key-Words: - Quantum Mechanics, Particle Swarm optimization, autopilots, nonlinear optimization, ship steering, PD control.

1 Introduction

An autopilot is a ship's steering controller, which automatically manipulates the rudder to decrease the error between the reference heading angle and the actual heading angle. One of the conventional autopilots is based on simple is PD control. In order to maintain the desired performance of PD-type autopilots, the control parameters must be adjusted in accordance with the variations of both ship dynamics and environment disturbances. Ship dynamics may vary due to operational conditions whereas disturbances are wind, waves, and currents, which also vary according to weather and sea conditions [1]. However, it is a tedious and difficult task to properly adjust the control parameters of the autopilot. To cope with the problems associated with parameter optimization of autopilots, the Particle Swarm Optimization algorithm (PSO) [2][3] is considered in this paper. PSO has been shown to be a promising approach for solving both unconstrained and constrained optimization problems [2][3][4][5]. Recently, several heuristics have been developed to improve the performance and set up suitable parameters for the PSO algorithm [2][3]. Some theoretical work to analyze the trajectory of particles has been carried out. A constriction factor has been proposed by Clerc and Kennedy [2] to ensure convergence. Trelea [3] reported on the trajectory analysis using dynamic systems theory. Another variant of PSO known as Gaussian Swarm [13] is proposed to minimize the number of control parameters in PSO while maintaining comparable performance. A quantum harmonic oscillator inspired version of the QOPSO algorithm was proposed very recently [6]. The QOPSO algorithm permits all particles to have a quantum behavior instead of the classical Newtonian dynamics that was assumed so far in all versions of PSO. Therefore, instead of the

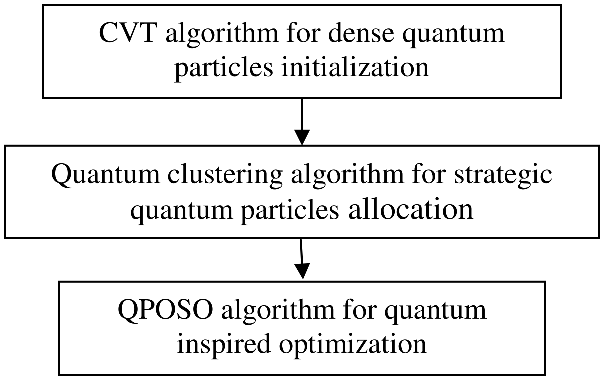

Figure 1. Framework of Quantum Potential Swarm Optimization

Newtonian random walk, some sort of "quantum trajectory" is imposed in the search process. One of the most attractive features of the new algorithm is the reduced number of control parameters, i.e. only one parameter required to be tuned in QOPSO. However the quantum-inspired PSO [6] demonstrated superior performance under the condition of large population sizes [6] and imposed additional variability in QOPSO performance results from the use of random starting configurations. The performance of QPOSO can be improved by strategically selecting the starting positions of the particles. It has been suggested the use of generators from Centroidal Voronoi Tessellation (CVT) as the starting points for the swarm can ensure the broad coverage of the search space and thus the solution space is fully explored for the optimal solution [7]. However, CVT relies on the large number of particles for a complete coverage of search space. In this paper, it is hypothesized that the response surface induced by the quantum particles consists of many quantum potential wells. The number of quantum particles generated from CVT can be reduced by selecting the minimal of quantum potential wells induced from quantum clustering technique [8]. The QOPSO framework is depicted in Fig. 1.

In Section II, the Quantum Oscillator based Particle Swarm Optimization (QOPSO) is explained. Centrodail Vornoi Tesselation (CVT) algorithm and Quantum Clustering (QC) are briefly described in Section III and Section IV. Section V presents the steering dynamics and control of a cargo ship model. Section VI discusses experimental results. Conclusion is presented in Section VII.

2 Quantum Oscillator Based Particle Swarm Optimization (QOPSO)

The QOPSO algorithm allows all particles to move under quantum-mechanical rules rather than the classical Newtonian random motion [6]. In quantum time-space framework, the quantum state of a particle is depicted by wavefunction $\Psi(\bar{x},t)$ and governed by the general time-dependent Schrodinger equation

$$ih\frac{\partial}{\partial t}\Psi(\bar{x},t)=\hat{H}\Psi(\bar{x},t) \qquad (1)$$

The operator $\hat{H}$ is the Hamiltonian operator. For a single particle of mass m in a potential field $V(\bar{x})$, it is given by

$$\hat{H}=-\frac{h^2}{2m}\nabla^2+V(\bar{x}) \qquad (2)$$

where h is Planck constant, m is the mass of the particle, and $V(\bar{x})$ is the potential energy distribution. It is hypothesized that the particle system that represents the search space, is a quantum system. Each particle is of quantum state formulated by wavefunction. An individual particle is assumed to move in a harmonic oscillator potential field in search space, of which center is point p. The harmonic oscillator potential field is attractive that eventually pull all particles to the point p. With point p the zero point of potential, the potential energy of the particle in one-dimensional harmonic oscillator field is represented as

$$V(x)=\frac{1}{2}kx^2 \qquad (3)$$

where k is a parameter defining the well "depth" or "strength". Again, this problem has the following well-known analytical solution [2]

$$\Psi_n(x)=\left(\frac{\alpha}{2^n n!\pi^{0.5}}\right)^{0.5}H_n(\alpha x)e^{-0.5\alpha^2x^2} \qquad (4)$$

Where $\alpha=\left(\frac{mk}{h^2}\right)^{\frac{1}{4}}$ and H_n is the Hermite polynomial with integer index n. Equation (4) shows that multiple possible eigen-states exists in this system. However, the problem can be simplified considerably by assuming that only the lowest possible mode (the ground state $n=0$, is available. In this case, the Gaussian probability can be obtained the Gaussian probability function [1]

$$Q(y)=\left|\Psi_0(y)\right|^2=\frac{\alpha}{\sqrt{\pi}}e^{-\alpha^2 y^2} \qquad (5)$$

The Q or $\left|\Psi_0(y)\right|$, the density function of probability that the particle appears at the position relative to p and $y=x-p$. Therefore, The updating equation can be derived as

$$\mathit{Initialize}\quad \mathbf{x}^m,\mathbf{P}^{\mathrm{m}}_{\mathrm{local}},\mathbf{P}_{\mathrm{global}}$$

$$\left(\begin{array}{l}\mathbf{P}^{\mathrm{m}}_{\mathrm{local}} \text{ is the local best vector of the mth parti} \\ \mathbf{P}_{\mathrm{global}} \text{ is the global best vector in the popul}\end{array}\right.$$

$$Do\ i=1,Max_{iteration}$$

$$Do\ m=1,N_{population}$$

$$\mathit{Update}\ \mathbf{P}^{\mathrm{m}}_{\mathrm{local}},\mathbf{P}_{\mathrm{global}}$$

$$\varphi_1=rand(0,1),\ \varphi_2=rand(0,1)$$

$$\mathbf{P}=\frac{\varphi_1\mathbf{P}^{\mathrm{m}}_{\mathrm{local}}+\varphi_2\mathbf{P}_{\mathrm{global}}}{\varphi_1+\varphi_2}$$

$$u=rand(0,1)$$

$$\beta=\left(\frac{\sqrt{2}}{g}\right)\left(\mathbf{x}^m-\mathbf{p}\right)$$

$$if\ \ rand(0,1)>5$$

$$\mathbf{x}^m=\mathbf{p}-\left(\beta\sqrt{\left(\ln\frac{1}{u}\right)}\right)$$

$$else$$

$$\mathbf{x}^m=\mathbf{p}+\left(\beta\sqrt{\left(\ln\frac{1}{u}\right)}\right)$$

$x=p\pm\frac{1}{\alpha}\sqrt{\ln\left(\frac{1}{u}\right)}$ where u is random number uniformly distributed on $(0,1)$. From convergence analysis in [1], it was shown

$$\beta=\frac{1}{\alpha}=\frac{\sqrt{2}}{g}\left|x-p\right| \qquad (6)$$

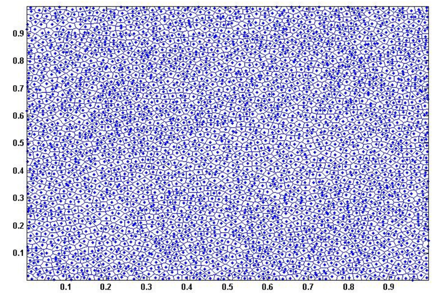

Figure 2. Centroidal Voronoi Tesselations for 3000 points

constrained by $g>0.75$. The control parameter β can be reduced to the selection of parameter g. $g=3$ is chosen in this paper. The QOPSO algorithm is summarized as follows:

3 Centroidal Voronoi Tessalations

A group of points in the search space is designed to be the set of solution generators. Particle initialization in PSO can be thought as a process to allocate the solution generators in the search space. The space is partitioned into compartments with particle as their centroid. The particles should be initialized so that they are distributed as evenly as possible throughout the space to ensure broad coverage of the search spaces. The standard method of particle initialization in standard PSO fails to accomplish this goal, especially in high-dimensional spaces [8]. Centroidal Voronoi Tessellation (CVT) is a way to partition a space into compartments [8]. It has been shown that CVT can initialize the PSO particles evenly in the solution space and lead to improved performance [8]. Two of the most well-known algorithms for computing CVTs are Mac Queen's method [8] and Lloyd's method [9]. Lloyd's algorithm is deterministic and requires only a few iterations, but each one is computationally expensive. In this paper, Lloyd's algorithm is chosen to compute CVT using the source codes available from the authors [9]. The details of the algorithm are explained in the literature [9]. Fig. 2 shows the CVTs for 3000 points of generators to be used as dense initial population of particles in QPOSO for the experiment to be discussed in this paper.

3 Quantum Clustering

The quantum clustering is a non-parametric clustering technique [8] based on non-parametric clustering technique. In this technique, it uses N data points, $x_1,\ldots,x_N$ to estimate the probability density function using the parzen-window estimator. The estimator is constructed by associating with each of the N points a Gaussian defined as in equation

$$\Psi(x)=\sum_{m=1}^{N} e^{-(x-x_m)^2/2\sigma^2} \tag{7}$$

The maxima of the function $\psi(x)$ haven been shown to occur at the cluster centers [10], where $1/2\sigma^2$ is the scale of the probability estimator. The function $\psi(x)$ is the Schroedinger Wave Function and performs a nonlinear transformation of the input space into Hilbert space. The motivation wish to view $\Psi(x)$ as an eigenstate of the time independent Schrodinger Wave equation [14], defines as in equation

$$\left(-\frac{1}{2\sigma^2}\nabla^2+V(x)\right)\Psi=E\Psi \tag{8}$$

where $V(x)$ is denoted the potential energy, E is denoted the energy eigenvalue and σ deduces the correct clustering of the space as it controls the width of the parzen-window. The parameter σ can be controlled to yield the relevant number of clusters. Given $\Psi(x)$ for any set of data points we can solve equation for $V(x)$:

$$V(x)=E+\frac{\left(\frac{1}{2\sigma^2}\right)\nabla^2\Psi(x)}{\Psi(x)} \tag{9}$$

If $V(x)$ is positive definite, that is in equation

$$E=-\min\frac{\left(\frac{1}{2\sigma^2}\right)\nabla^2\Psi(x)}{\Psi(x)} \tag{10}$$

As the lowest eigenstate of the time independent Schrondinger Wave equation, E is the minimal eigenvalue of V. The lowest possible eigenvalue occurs for the harmonic potential in which case $E=d/2$. This leads to the inequality (11).

$$0<E\le\frac{1}{2}d \tag{11}$$

In quantum clustering, the cluster centers are obtained while searching for the minima of the potential functions. One may locate the cluster centers, and deduce the clustering allocation of the data, by following the dynamics of gradient descent into the potential minima. Assuming that $u^m(x^s)$ is the probability that x^s belongs to the cluster of points represented by the vector v^m. By defining $v^m(0)=x_m$, one follows the steps of

$$v^m(t)=v^m(t-1)-\eta(t)\nabla V\left(v^m(t)\right) \tag{12}$$

letting the points reach an asymptotic fixed value coinciding with a clustering center. In this paper, the Gaussian function $\Psi(x)$ from equation (7) is generalized to allow for different weighting of different points, as in

$$\Psi(x)=\sum_{m=1}^{N} c_m e^{-(x-x_m)^2/2\sigma^2} \tag{13}$$

with $c_m\ge 0$. The c_m is calculated by the fitness function in Quantum Oscillator based Particle Swarm Optimization (QOPSO) algorithm, for emphasizing or deemphasizing the influence of data points based their fitness value. Therefore, the 3000 quantum particles generated by CVTs is reduced to 30 by the quantum clustering algorithm based on the minimal eigenvalues of V as shown in Fig. 3.

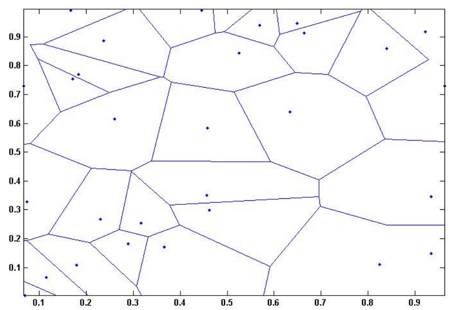

Figure 3. Voronoi diagram of 30 quantum potential particles extracted from quantum clustering

4 PD Control of Cargo Ship Steering

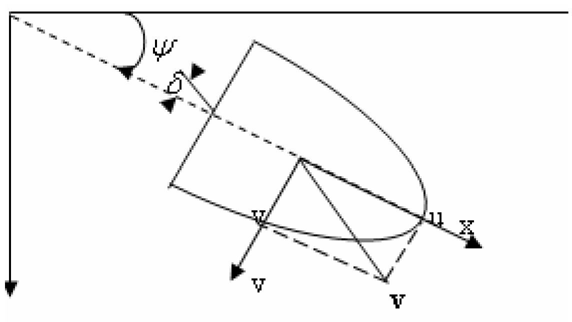

Figure 4. Cargo Ship

Assuming the "bobbing" or "bouncing" effects of the ship is neglected for large vessels, the motion of the ship is described by a coordinate system which is fixed to the ship [10]. Based on Fig. 4, a simple model which describes the dynamical behavior of the ship can be expressed by the following differential equation:

$$\dddot{\psi}(t)+\left(\frac{1}{\tau_1}+\frac{1}{\tau_2}\right)\ddot{\psi}(t)+\left(\frac{1}{\tau_1}\frac{1}{\tau_2}\right)\dot{\psi}(t) = \frac{K}{\tau_1\tau_2}\left(\tau_3\dot{\delta}(t)+\delta(t)\right) \tag{14}$$

where ψ is the heading of the ship and δ is the rudder angle. Assuming zero initial conditions, (14) can be written

$$\frac{\phi(s)}{\delta s}=\frac{K\left(s\tau_3+1\right)}{s\left(s\tau_1+1\right)\left(s\tau_2+1\right)} \tag{15}$$

where K,τ_1,τ_2 and τ_3 are parameters which are a function of the ship's constant forward velocity u and its length l as expressed below:

$$K=K_0\left(\frac{u}{l}\right) \tag{16}$$

$$\tau_i=\tau_{i0}\left(\frac{l}{u}\right), \quad i=1,2,3. \tag{17}$$

where we assume that for a cargo ship $K_0=-3.86, \tau_{10}=5.66, \tau_{20}=0.38, \tau_{30}=0.89$, and $l=161$ m [12]. The ship is assumed to travel in the x direction at a velocity of 5m/s. The model in (5) is obtained by linearizing the equations of motion around the zero rudder angle $(\delta=0)$. This is only valid if the ship make small deviations from a straight line path, $(\delta<5^{\circ})$. For $\delta>5^{\circ}$, an extended model given as follows should be used [11].

$$\dddot{\psi}(t)+\left(\frac{1}{\tau_1}+\frac{1}{\tau_2}\right)\ddot{\psi}(t)+\left(\frac{1}{\tau_1}\frac{1}{\tau_2}\right)H\left(\dot{\psi}(t)\right) = \frac{K}{\tau_1\tau_2}\left(\tau_3\dot{\delta}(t)+\delta(t)\right) \tag{18}$$

where $H\left(\dot{\psi}(t)\right)$ is a nonlinear function of $\dot{\psi}(t)$. The function is approximated as equation (19) under steady state condition, $\dddot{\psi}=\ddot{\psi}=\delta=0$.

$$H(\dot{\psi})=a\dot{\psi}^3+b\dot{\psi} \tag{19}$$

where a and b are real valued constants such that a is always positive. They are chosen to be 1 in this paper.

A direct PD controller is used for the cargo ship steering. The PD-type control law which will be employed for this process may be expressed by

$$\delta(t)=k_p\left(\psi_r(t)-\psi(t)\right)-k_d\dot{\psi}(t) \tag{20}$$

The reference model for this process is chosen to be

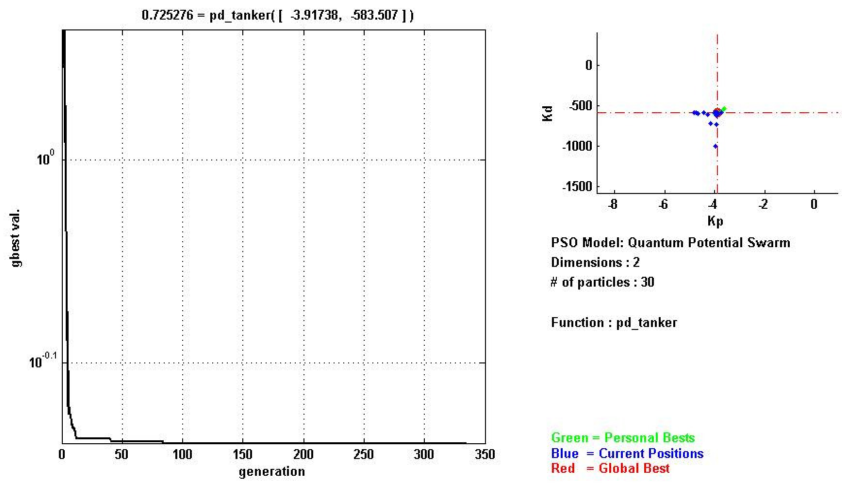

Figure 5. Result for the PD controller optimization of cargo ship steering using Quantum Potential Swarm (QPOS) model.

Table 1 Summary of results

PSO model	Kp	Kd	gbest (J)
Clerc[2]	-3.789	-563.78	0.7280
Trelea[3]	-3.894	-575.72	0.7239
Gaussian[13]	-3.683	-547.90	0.7339
QPOSO	-3.917	-583.51	0.7253

$$\psi_m(t) = \frac{\omega_n}{p^2 + \zeta\omega_n p + \omega_n^2}\psi_r(t) \qquad (21)$$

In the simulation, $\zeta = 1, \omega_n = 0.05$ are chosen. The PD controller parameters, k_p and k_d are optimized by PSO to minimize the following cost function which represents the propulsive energy losses due to steering.

$$J = \frac{1}{T}\left[\sum_{t=1}^{T}\left(e(t)^2 + \lambda\delta(t)^2\right)\right] \qquad (22)$$

The λ is set to 0.01 in the simulation.

5 Experimental Results

For the comparative analysis for QPOSO model with three other latest PSO models (Clerc[2], Trelea[3] and Gaussian[14]), the nonlinear process model given in equation (18) is used to emulate the "real" ship dynamics. The QPOSO models will perform the PD controller optimization based on the cost function defined in equation (22). The QPOSO algorithms were implemented using the PSO toolbox in Matlab [12]. During the numerical experiments, QPOSO models were run with an initial population of particles generated by quantum clustering shown in Fig. 3. All the running trials were carried out with a population of 30 particles and 200 generations. From the results obtained, it can be observed that the QPOSO model shows better accuracy than Clerc and Gaussian models and comparable to Trelea model. The result presented is still preliminary, but show clearly the QPOSO model has the ability to optimize the PD controller of cargo ship steering. The optimization curve is shown in Fig. 5. Table 1 summarizes the results. Fig. 6(a) and 6(b) depict the dynamic response of the PD controlled cargo ship based on optimization of QPOSO model.

6 Conclusion

A unified framework for quantum inspired particle swarm optimization named as Quantum Potential Swarm Optimization (QPOSO) is proposed for the study of PD controller optimization for the cargo ship steering system. The QPOSO integrates the ideas from Quantum Oscillator Particle Swarm Optimization (QOPSO), Quantum Clustering (QC) and Centroidal Voronoi Tessellation (CVT) for a complete solution for the particles initialization problems in standard PSO. QPOSO is tested and able to outperform other three latest PSO models. Despite the highly nonlinear characteristics of cargo ship dynamics, QPOSO has shown its ability to optimize the PD controller to minimize the propulsive energy losses due to steering. The ship heading error is effectively minimized. The promising results in this paper clearly indicate that QPOSO can be an effective tool to optimize the steering control of cargo ship and other naval engineering applications.

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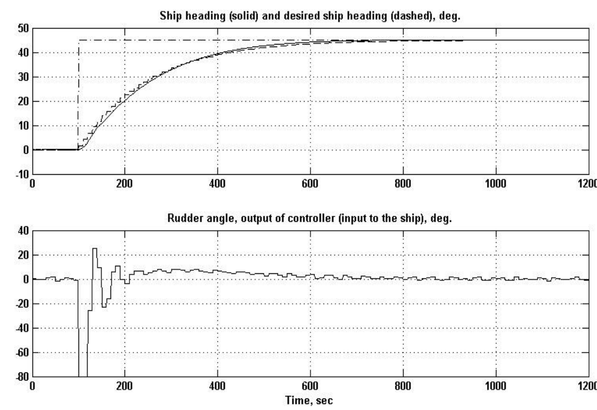
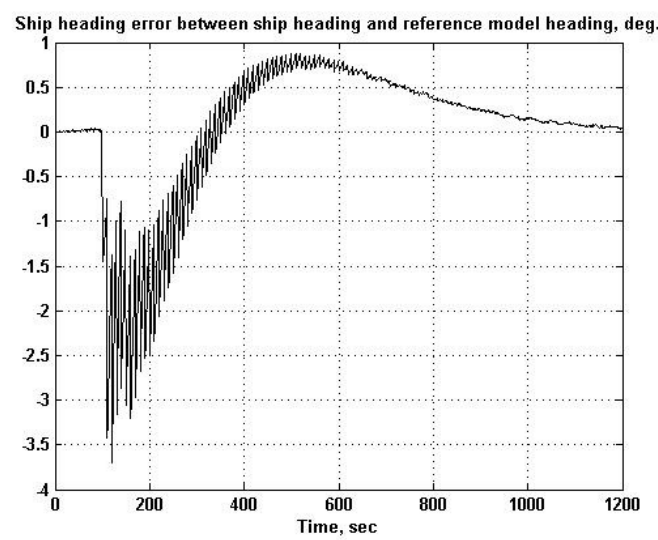


(a)



(b)

Figure 6. (a) The step response and rudder angle of cargo ship steering control based on optimization of Trelea PSO model. (b) Ship heading error and reference model heading