Research Article

Multiparameter Adaptive Optimisation of MSE Osseous Expansion Position

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Received 28 December 2021; Accepted 25 February 2022; Published 6 April 2022

Academic Editor: Nagarajan Deivanayagampillai

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The accuracy of the implantation position of the MSE osseous expansion anchorage implant is a key issue in the treatment of osseous expansion, which also suffers from the drawback of falling into prematureness too early when the standard QPSO algorithm is used for its multiobjective optimisation. In this study, an adaptive improved QPSO algorithm is proposed to address the above problems. Firstly, a partitioned retrieval strategy is used to divide the population into an auxiliary class group and a main iterative population, and the respective search iteration intervals of the populations are assigned, thus optimising the initialisation mechanism of the standard algorithm, and then, the pheromone mechanism in the ACO algorithm is introduced to make the particles in the QPSO algorithm carry pheromones, and the particles determine their direction of travel by sensing the pheromone concentration in each path, thus improving the search ability of the particles. Experimental simulation results show that the improved strategy proposed in this study effectively improves the population diversity of the standard QPSO algorithm, avoids the algorithm from entering local optimum, and has good application in MSE osseous expansion position optimisation.

1. Introduction

The MSE (maxillary skeletal expander), also known as microimplant brace-assisted rapid maxillary expansion, is characterised by its reliance on four BMK anchorage implants in the maxilla, which act directly on the midpalatal suture with the aid of the anchorage implants to open the midpalatal suture and widen the upper arch by drawing the bone, effectively avoiding the tilt compensation associated with traditional expansion devices with the lack of sufficient skeletal effect [1–3]. However, the implant position of the anchorage implants is currently determined by the surgeon’s own experience, so the rapid and accurate acquisition of the optimal implant position has become an urgent problem.

Studies on the optimisation of MSE osseous expansion position have been less reported in the domestic and international literature, mostly on the analysis of the effect of MSE osseous expansion. Paredes et al. [4] evaluated the differences in bone, alveolar bone, and tooth composition induced by the osseous expander in the middle of the microimplant-supported surface, and Moon et al. [5] studied the molar inclination and the surrounding alveolar bone changes after MSE osseous expansion by CBCT. Abedini et al. [6] analysed and studied the changes in the human facial soft tissues after MSE osseous expansion. Hartono et al. [7] performed a finite element analysis of the palatal alveolar bone, palatal suture, zygomatic suture, microbone, and the surrounding bone of the first molar after MSE osseous expansion implantation. Cantarella et al. [8] improved the implant position of MSE based on biomechanics. Giudice et al. [9] optimised the implantation parameters of four BMK anchorage implants to improve their stability.

Optimisation of the MSE osseous expansion position is essentially a multiobjective optimisation process, and the QPSO (quantum-behaved particle swarm optimisation) algorithm is a common multiobjective optimisation algorithm currently available. QPSO algorithm has effective applications in various fields, such as parameter selection in industrial manufacturing [10, 11], image segmentation [12], and prediction problems in systems such as SLAM [13, 14].
Kumar et al. [15] proposed an improved QPSO algorithm based on constrained optimisation to improve the multiobjective optimisation performance. Guo et al. [16] used a multilevel perturbation strategy to optimise the QPSO algorithm to improve the convergence performance and search range. Zhang et al. [17] proposed a quantum-behaved particle swarm algorithm based on generalised space transform search, which solved the problem of premature convergence of the standard algorithm. Grotti et al. [18] proposed an improved QPSO algorithm based on multiobjective archiving, which optimised the multiobjective optimisation effect. Dong et al. [19] used BP neural networks to improve the QPSO algorithm, solving the problems of slow convergence and easy oscillation. Chen et al. [20] proposed a hybrid quantum algorithm based on generalised space transform search, which solved the problem of prematureness exhibited by the standard QPSO algorithm in the application of MSE osseous expansion position optimisation. The initialisation mechanism is optimised using a partitioned retrieval strategy, and the search capability of the standard algorithm is improved using a pheromone mechanism, thus reducing the probability of early falling into prematureness of the standard QPSO algorithm.

In this study, an adaptive improved QPSO algorithm is proposed to address the phenomenon of early falling into prematureness exhibited by the standard QPSO algorithm in the application of MSE osseous expansion position optimisation. The initialisation mechanism is optimised using a partitioned retrieval strategy, and the search capability of the standard algorithm is improved using a pheromone mechanism, thus reducing the probability of early falling into prematureness of the standard QPSO algorithm.

2. The Multiobjective Optimisation Model for MSE Osseous Expansion Position

2.1. The Parametric Mapping Model for the MSE Osseous Expansion Position. In order to obtain the optimal position of the MSE osseous expansion, the width of the midpalatal suture at the cusp (SOC) \( x_1 \), the maxillary basal bone width (WMB) \( x_2 \), the width of the midpalatal suture at the molar (SOM) \( x_3 \), the nasal width (NW) \( x_4 \), the maxillary alveolar bone width (MAW) \( x_5 \), the intermolar width of palatal root (IWR) \( x_6 \), the molar buccal cusp width (IWC) \( x_7 \), the inclination of the right molar \( x_8 \), the inclination of the left molar \( x_9 \), and the molar palatal cusp angle \( x_{10} \) were first selected as variable factors to construct a parametric mapping model based on quantum behaviour, as shown in Figure 1. The methods for obtaining the variable factors are shown in Table 1.

On the basis of the above variable factors, a dataset of the optimal MSE osseous expansion position was collected for each case, containing the three-dimensional spatial positions A, B, C, and D of the four implants, as shown in Figure 2.

Let the set of parameters for the optimal MSE osseous expansion position be \( f(x) \); then, the parametric mapping model for the MSE osseous expansion position can be expressed as

\[
\begin{align*}
  f(x) = & \{a_1x_1, a_2x_2, \ldots, a_{10}x_{10}\},
\end{align*}
\]

where \( a_i \ (i = 1, 2, \ldots, 10) \) is the parameter variation factor.

2.2. QPSO-Based Parametric Multiobjective Optimisation. In this study, QPSO is used for multiobjective optimisation of the parametric mapping model based on quantum behaviour. Unlike the PSO algorithm, the QPSO algorithm no longer depends on the position and velocity of the individuals for its current population state during the update and iteration process. In quantum space, because of the particle and fluctuating nature of individual particles, the quantum behaviour of particles cannot be described by definite values of particle position and particle velocity as in the PSO algorithm, so instead of particle position and velocity, wave functions are used. Since the intensity of the wave function at a point in quantum space is proportional to the probability density of the particle’s appearance, it is shown in equation (2) as

\[
|\psi(X,t)|^2 \, dx \, dy \, dz = Q \, dx \, dy \, dz,
\]

where \( X \) is the position vector of the particle in the quantum space, \( Q \) is the probability density function, and \( \psi(X,t) \) is the wave function, while the probability density function should satisfy the normalization condition:

\[
\int \int \int |\psi(X,t)|^2 \, dx \, dy \, dz = \int \int \int Q \, dx \, dy \, dz = 1.
\]

The control of particle motion is achieved by solving Schrödinger’s equation to obtain the probability density function and probability distribution function for the appearance of a particle at a point in space, as shown in equations (4) and (5):

![Figure 1: Illustration of the measurement method of the variable factors.](image-url)
the population best position are calculated as problemsolution; then, the position of the $i$th particle population consist of interval (0, 1). In a iteration can be expressed as equation for the position update of the particle in classical space. Monte Carlosimulation is used to solvethe objective of the multiobjective optimisation is to find the optimal MSE osseous expansion position, the set of parameters for its optimal parameter change factor so that the deviation of the

$$Q(X) = |\psi(X)|^2 = \frac{1}{L^2} \frac{2|X - p|}{L},$$  \quad (4)

$$F(X) = 1 - e^{-\frac{2|X - p|}{L}},$$  \quad (5)

where $p$ is the particle attractor, $L$ is the potential well \(\delta\) length, and $X$ denotes the particle position.

In order to solve the change from quantum search space to classical space, Monte Carlo simulation is used to solve the equation for the position update of the particle in classical space. The particle is moved inside a potential well centred on $p$, and its position is determined by

$$X = p \pm \sqrt{\frac{2}{L}} \ln \frac{1}{u},$$  \quad (6)

where $u$ is a random number uniformly distributed on the interval (0, 1). In a $D$-dimensional search space, let the particle population consist of $N$ particles with a potential problem solution; then, the position of the $i$th particle at the $t$ iteration can be expressed as

$$X(t) = \{X_{i,1}(t), X_{i,2}(t), \ldots, X_{i,D}(t)\},$$  \quad (7)

where the range of $i$ is 1 ~ $N$.

In the QPSO algorithm, the individual best position and the population best position are calculated as

$$\left\{ \begin{array}{l}
P_{i}(t) = \{P_{i,1}(t), P_{i,2}(t), \ldots, P_{i,D}(t)\}, \\
G(t) = \{G_{1}(t), G_{2}(t), \ldots, G_{N}(t)\}.
\end{array} \right.$$  \quad (8)

When the particle $i$ is in $t + 1$ iteration, then the position of the particle can be expressed according to equation (6) as

$$x_{i,d}(t + 1) = p_{i,d}(t) \pm \frac{L_{i,d}(t)}{2} \ln \frac{1}{u_{i,d}(t)},$$  \quad (9)

where $L_{i,d}(t)$ is then expressed by

$$L_{i,d}(t) = 2\alpha(t) \{C_{d}(t) - x_{i,d}(t)\},$$  \quad (10)

where $\alpha$ is the constriction-broadening factor and $C_{d}(t)$ is the average optimal position, which is the centroid of all particles’ own optimal positions and can be determined from

$$C(t) = \frac{1}{N} \sum_{i=1}^{N} P_{i}(t).$$  \quad (11)

Thus, the equation for the evolution of the position update of the particle is obtained as

$$x_{i,d}(t + 1) = p_{i,d}(t) \pm \alpha(t) |C_{d}(t) - x_{i,d}(t)| \ln \frac{1}{u_{i,d}(t)}.$$  \quad (12)

Combined with the parametric mapping model of the MSE osseous expansion position, the set of parameters for its optimal MSE osseous expansion position is $f(x)$. The objective of the multiobjective optimisation is to find the optimal parameter change factor so that the deviation of the

| Factor variables | Measurement methods |
|------------------|---------------------|
| $x_{1}$          | Distance between a point on each side of the midpalatal suture corresponding to the bilateral cusps |
| $x_{2}$          | Width across the buccal cusp of the right and left first premolar |
| $x_{3}$          | Distance between a point on each side of the midpalatal suture corresponding to the bilateral maxillary first molars |
| $x_{4}$          | Maximum width of the nasal part at the first maxillary molar level on both sides |
| $x_{5}$          | Distance between the lowest points of the alveolar bone on the buccal side of the first maxillary molar level, bilaterally |
| $x_{6}$          | Distance between the points of the palatal roots on each side of the first maxillary molar level, bilaterally |
| $x_{7}$          | Distance between the points of the buccal cusps on both sides at the first maxillary molar level bilaterally |
| $x_{8}$          | Medial angle between the line of the buccal cusp of the right molar and the cusp of the palatal root and the palatal plane |
| $x_{9}$          | Medial angle between the line of the buccal cusp of the left molar and the cusp of the palatal root and the palatal plane |
| $x_{10}$         | The angle between the extension of the line between the buccal cusp of the right molar and the tip of the palatal root and the extension of the line between the buccal cusp of the left molar and the tip of the palatal root |

Figure 2: Optimal MSE osseous expansion position.
MSE osseous expansion position is minimised; therefore, the specific process of its multiobjective optimisation is as follows:

Step 1: input the parameter variation factor into the algorithm and initialize the population, randomly generating $N$ particles
Step 2: calculate the average optimal position of the population particles
Step 3: calculate the current individual fitness function value of each particle, and update it if it is better than or less than the individual fitness function value of the particle in the last iteration
Step 4: calculate the global optimal position in the population
Step 5: for each dimension of the particles in the population individuals, calculate the position of a random point
Step 6: perform the evolution of the position update according to equation (12)
Step 7: if it is satisfied, then end the update and iteration to obtain the optimal parameter change factor

2.3. Algorithm Simulation Test. Simulation experiments were conducted on the QPSO-based parametric multiobjective optimisation strategy, and the optimal position error obtained by the algorithm was set as the evaluation value, and three sets of experimental data were used for the optimisation search test, as shown in Table 2.

The test results of the QPSO algorithm are shown in Figure 3.

Based on the above experimental results, it can be seen that the QPSO algorithm shows excellent search performance in the early stage of the algorithm, but falls into local optimum in the middle stage.

3. Search Performance Optimisation of QPSO Algorithm

3.1. Initialisation Mechanism Based on Partitioned Search. Without degrading the convergence performance of the algorithm, a new initialisation strategy is proposed in this study in order to improve the quality of each particle and the diversity at the late stage of the population.

Based on two types of populations, the auxiliary population and the main iterative population, the auxiliary population is defined as $\hat{X}_s$, satisfying $1 \leq i \leq m$, and $m$ is the number of auxiliary populations. Meanwhile, the main population is defined as $\hat{X}$.

In order to create the main iterative population $\hat{X}$, each auxiliary population $\hat{X}_i$ is given a random initialisation. As a result, such random initialisation throughout the search space leads to the generation of diverse populations in uncertain regions with high quality for each particle in the population.

The auxiliary populations are updated and moved according to the basic method of the QPSO algorithm, and then, the globally optimal individuals of each auxiliary population $\hat{X}_i$ are added to the main population $\hat{X}$. The basic steps for creating the main population $\hat{X}$ are shown in Figure 4.

The search space is then partitioned into a number of zones and the auxiliary populations are initialised in the search intervals of these partitions. The partitioning strategy follows a better coverage of the optimised area, resulting in a good view of each auxiliary search interval. The whole partition $[\min, \max]$ is divided into several iterative search regions with a total number of $\max_\beta$ auxiliary intervals, and a start node of the partitioning process is defined as the centre of the search region.

To define the boundaries of each partitioned region, calculate the step size and centre of each partitioned region according to equations (13) and (14):

$$\text{center} = \frac{(\max - \min)}{2}, \quad (13)$$

$$\text{step} = \frac{\text{center}}{\max_\beta} \quad (14)$$

The total number of each partitioned region is then solved according to equations (15) and (16):

$$\text{zone}_{\text{imin}} = \text{center} - \text{zone}_\beta \times \text{step}, \quad (15)$$

$$\text{zone}_{\text{imax}} = \text{center} + \text{zone}_\beta \times \text{step}, \quad (16)$$

where $\text{zone}_\beta$ is the current number of populations, i.e., $\text{zone}_\beta = 1, 2, \ldots, \max_\beta$. The partitioned search space is depicted in Figure 5.

Different partitioned intervals have different sizes and the size of the auxiliary population $\hat{X}_i$ is defined as $\hat{X}_i$, which is based on the size of the corresponding search interval. The size of the partition interval follows the principle that the smaller the search space, the fewer individuals in the search space, and conversely, the larger the search interval, the more individuals in the search space. Then, the size of the partition interval is shown as

$$\hat{X}_i = \text{zone}_\beta \times H_\beta, \quad (17)$$

where $\text{zone}_\beta$ is the number of particles in each auxiliary partition and $H_\beta$ is a fixed value, which in this study is taken as 2.

3.2. Pheromone Mechanism-Based Search Capability Optimisation. In order to further improve the search capability of the QPSO algorithm, the pheromone mechanism in the ACO algorithm is introduced in this study, so that the particles in the QPSO algorithm carry pheromones. The state of a particle can be represented by the wave function $\psi(Y)$:

$$L = \frac{h^2}{m \tau}, \quad (18)$$

$$\psi(Y) = \frac{1}{\sqrt{L}} e^{-\frac{|Y|}{L}}, \quad (19)$$
where each particle can release pheromones; \( r_{ij}(t) \) indicates the content of pheromones on the path \((i, j)\) of the particle at the moment \( t \) and sets to start with the same content of pheromones on the path. The particle decides the direction of its travel by sensing the pheromone concentration on each path, and the next position shift is influenced by both the

### Table 2: Simulation test datasets.

| Factor variables | Case 1       | Case 2       | Case 3       |
|------------------|--------------|--------------|--------------|
| \( x_1 \)        | 3.3          | 0.9          | 4.2          |
| \( x_2 \)        | 62.5         | 60.6         | 63.9         |
| \( x_3 \)        | 1.3          | 1.5          | 2.2          |
| \( x_4 \)        | 31.4         | 36.3         | 35.1         |
| \( x_5 \)        | 55.9         | 55           | 62           |
| \( x_6 \)        | 39.9         | 37.7         | 36.7         |
| \( x_7 \)        | 57.6         | 52.2         | 58.2         |
| \( x_8 \)        | 119.9        | 113.3        | 127.6        |
| \( x_9 \)        | 120          | 120.5        | 132.6        |
| \( x_{10} \)     | 59.9         | 53.8         | 80.2         |

\[ A \quad (-188.66, -186.56, 43.50) \quad (-196.79, -200.15, 33.99) \quad (-190.51, -190.51, 43.50) \]

\[ B \quad (-176.83, -185.40, 43.50) \quad (-185.02, -200.53, 33.99) \quad (-173.98, -180.21, 43.50) \]

\[ CD \quad (-188.49, -193.12, 43.50) \quad (-196.93, -205.83, 33.99) \quad (-185.84, -188.31, 43.50) \]

\[ (-176.66, -191.94, 43.50) \quad (-185.16, -206.21, 33.99) \quad (-178.61, -178.61, 43.50) \]

\[ \]

Figure 3: Optimisation simulation results for the three datasets. (a) Optimal implant position search results for case 1. (b) Optimal implant position search results for case 2. (c) Optimal implant position search results for case 3.
In this study, we use the average of all the particles’ individual optima mbest, which is the average best position, i.e.,

$$m_{best} = \frac{1}{M} \sum_{i=1}^{M} p_i(t),$$

(21)

where the characteristic length $L$ is

$$L_{i,j}(t) = 2\alpha \cdot |m_{best} - X_{i,j}(t)|,$$

(22)

where $\alpha$ is the constriction-broadening factor, which usually works better when decreasing linearly from 1.0 to 0.5, so we have

$$\alpha = 1 - \frac{0.5t}{T},$$

(23)

where $t$ is the current number of evolutionary generations and $T$ is the number of terminating evolutionary generations.

The evolution equation for its particles becomes

$$X_{i,j}(t + 1) = p_{i,j}(t) \pm \alpha \cdot |m_{best} - X_{i,j}(t)| \cdot \ln \frac{1}{u_{i,j}(t)},$$

(24)

where $p_{i,j}(t)$ is the centre of the potential well of the $i$th particle in the $j$th dimension:

$$p_{i,j}(t) = \varphi(t) \cdot P_{i,j}(t) + \left[1 - \varphi(t)\right] \cdot G_j(t).$$

(25)

4. Algorithm Simulation and Application Testing

4.1. Performance Simulations of the Improved QPSO Algorithm. In order to verify the performance of the improved QPSO algorithm, simulation tests were carried out. The optimal position error obtained by the algorithm was set as the evaluation value, and three sets of experimental data were used for the optimisation test, as shown in Table 3.

The results of the optimisation search tests of the improved QPSO algorithm are shown in Figure 6.

From the above simulation results, it can be seen that the improved QPSO algorithm proposed in this study, due to the optimisation of the initialisation mechanism and the search capability, improves the population diversity and avoids the algorithm from entering into local optimum.

4.2. Application of the MSE Osseous Expansion Position. In order to test the application performance of the improved QPSO algorithm proposed in this study, the detection parameters of the cases were optimised to obtain the best MSE osseous expansion position, and the detection parameters of the cases are shown in Table 4.

The results of the improved QPSO are shown in Figure 7, and the best MSE osseous expansion positions obtained are A (−198.44, −203.31, 33.71), B (−186.64, −202.35, 33.71), C (−197.71, −208.77, 33.71), and D (−186.01, −207.70 33.71); the actual optimal MSE osseous expansion positions were A (−198.36, −203.38, 33.71), B (−186.60, −202.30, 33.71), C
Table 3: Simulation test datasets.

| Variable factor | Case 4       | Case 5       | Case 6       |
|-----------------|--------------|--------------|--------------|
| x₁              | 2.5          | 4.4          | 2.7          |
| x₂              | 59.6         | 58.1         | 59           |
| x₃              | 1.4          | 2.0          | 1.9          |
| x₄              | 32.9         | 30.9         | 30.7         |
| x₅              | 48.7         | 53.0         | 51.6         |
| x₆              | 32.1         | 33.9         | 32.6         |
| x₇              | 48.0         | 50.7         | 48.6         |
| x₈              | 119.5        | 131.5        | 130.2        |
| x₉              | 122.5        | 136.9        | 123.3        |
| x₁₀             | 62.0         | 88.4         | 73.5         |

\[ A = (-194.49, -202.39, 40.77) \]
\[ B = (-194.49, -202.39, 40.77) \]
\[ C = (-194.45, -207.56, 40.77) \]

Figure 6: Optimisation simulation results for the three datasets. (a) Optimal implant position search results for case 4. (b) Optimal implant position search results for case 5. (c) Optimal implant position search results for case 6.
\[ e = \sqrt{(A - A')^2 + (B - B')^2 + (C - C')^2 + (D - D')^2}, \]

where \((A, B, C, D)\) is the optimal MSE osseous expansion position found by the improved QPSO algorithm and \((A', B', C', D')\) is the actual optimal MSE osseous expansion position.

Therefore, the error of the improved QPSO algorithm in finding the optimal MSE osseous expansion positions for this case is 0.0975, which is much smaller than that of the standard QPSO algorithm of 0.3959, reflecting the superiority of the improved QPSO algorithm proposed in this study.

5. Summary

The optimal MSE osseous expansion arch position is obtained by the computer intelligence algorithm, and a mathematical model is established to produce implant guides using 3D printing technology, which helps to improve the success rate of MSE treatment and reduce its risk. In this study, an adaptive improved QPSO algorithm is proposed to address the problem that the multiobjective optimisation process of the standard QPSO algorithm for the parametric mapping model of MSE osseous expansion position is prone to local optimum, and the experimental simulation results show that the improved QPSO algorithm proposed in this study has better multiobjective optimisation performance and is well applied in the optimisation of MSE osseous expansion position.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the Zhejiang Research and Development program (no. 2021C03075).

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