Cultural firework algorithm and its application for digital filters design

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Abstract: The substance of the digital filter design is a multi-parameter optimisation problem. This paper presents a joint objective function to design finite impulse response (FIR) digital filters and infinite impulse response (IIR) digital filters, and a cultural firework (CF) algorithm is proposed to implement filter designs. The design of the filter is transformed into the constrained optimisation problem, and the cultural firework algorithm is used to search optimal value of filter design parameters in the parameter space with parallel search. The proposed cultural firework algorithm is a multi-dimensional search algorithm for optimisation of real numbers, which uses mechanisms of cultural evolution to update the locations of cultural sparks. Computer simulations have showed that FIR and IIR digital filters based on the CF algorithm are superior to previous filters based on particle swarm optimisation (PSO), quantum-behaved particle swarm optimisation (QPSO) and adaptive quantum-behaved particle swarm optimisation (AQPSO) in the convergence speed and optimisation results. The effectiveness and superiority of the CF are also demonstrated by computer simulations.

Keywords: cultural firework algorithm; fireworks algorithm; FA; cultural algorithm; CA; FIR digital filter; IIR digital filter; filter design.

Reference to this paper should be made as follows: Gao, H. and Diao, M. (xxxx) ‘Cultural firework algorithm and its application for digital filters design’, Int. J. Modelling, Identification and Control, Vol. X, No. Y, pp.000–000.

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1 Introduction

Finite impulse response (FIR) and infinite impulse response (IIR) filters have widespread application in all kinds of engineering problems (Hu, 2003). In the past, researchers have applied simulated annealing (SA) approach (Nevio et al., 1992), genetic algorithms (GA) (Li and Yin, 1996; Xu and Daley, 1995), particle swarm optimisation (PSO) (Li et al., 2005; Chen and Luk, 2010), chaos PSO (CPSO) algorithm (Gao et al., 2008), quantum PSO (QPSO) (Fang et al., 2006) and adaptive QPSO (AQPSO) (Fang et al., 2008) to the design of FIR filters or IIR filters. As we know, SA has expensive complexity for digital filter design. Implementation of GA algorithm is complex and the convergence speed is slow for parameters design of FIR filter. PSO and some improved PSO algorithms are random search algorithms and have been applied to many optimisation problems. However, as demonstrated by Van Den Bergh (2001), PSO is not a global convergent algorithm. So, it is worthy to design a novel intelligence algorithm with high performance for FIR and IIR filters.

The natural system that has developed for so long is one of the rich sources of inspiration for inventing new intelligent algorithms. Inspiring intelligence algorithms are important scientific fields that are closely related to physical and biological phenomenon existing in nature, and some algorithms are widely studied for application, such as PSO (Yuan and Chen, 2010; Tian et al., 2009), ant colony optimisation/PSO (Zhang et al., 2009), bacterial swarming algorithm (Wu et al., 2010), differential evolution algorithm (Wong and Dong, 2005; Neri and Caponio, 2010) and cultural algorithm (CA) (Reynolds and Zhu, 2001). CA is an effective intelligence method for real number optimisation. Initially, CAs were applied with population spaces based on
evolutionary programming (Reynolds and Chung, 1996) approaches to real parameter optimisation. Recently, PSO has also been proposed as a population space (Iacoban et al., 2003). In some literatures (Reynolds and Chung, 1996; Reynolds and Zhu, 2001), the belief space is divided into four-knowledge sources: situational, normative, topographical, and historical knowledge. Last year, new optimisation concepts of fireworks algorithm (FA) (Tan and Zhu, 2010) are proposed as a novel intelligence algorithm for optimisation problem. Therefore, inspired from the previous intelligence computation, we design new algorithm based on CA and FA for FIR and IIR filters to solve the disadvantages of previous intelligence filters.

2 Our approach

This paper proposed a cultural firework (CF) algorithm which is based on a FA and a CA for the optimisation design of FIR and IIR digital filters. Four types of cultural spark locations are generated to keep the diversity of cultural sparks, and hybrid of two different of selection process for locations is a effective mechanism for keeping diversity. Therefore, the CF algorithm has the capability of avoiding premature convergence.

To validate the performance of the proposed CF algorithm, comparison experiments were conducted on FIR and IIR digital filter among the CF, the PSO, the QPSO and the AQPSO. It is shown that the CF algorithm clearly outperforms the PSO, the QPSO and the AQPSO in optimisation accuracy and convergence speed.

This paper will focus on the implementation of FIR and IIR digital filters based on the CF algorithm. The rest of the paper is organised as follows. Then, in Section 3, CA is introduced and the CF algorithm is proposed in detail. In Section 4, models of FIR and IIR digital filter are presented, and the applications of the CF to FIR and IIR digital filters design are presented. Then, in Section 5, the experiment results for FIR and IIR filter design are given. At last, some conclusions and remarks are given in Section 6.

3 CF algorithm

Suppose the CF algorithm is designed for the general optimisation problem:

$$\hat{x} = \arg \min_x f(x)$$

where $x = (x_1, x_2, \ldots, x_n)$ denotes a location in the potential space, $x_{\text{min}} \leq x_i \leq x_{\text{max}}$ ($i = 1, 2, \ldots, m$), $f(x)$ is an objective function, $x_{\text{min}}$ and $x_{\text{max}}$ denote the bounds of the potential variants.

3.1 Knowledge updating of CF algorithm

The key idea of cultural FA is to acquire problem-solving knowledge (beliefs) from the explosion of fireworks and in return make use of that knowledge to fireworks population and guide the search. For designing cultural FA, we will firstly introduce some basic concepts of CA, which are base of the proposed CF algorithm.

Belief space defined in this paper is given by $s$ and $N_i$ ($i = 1, 2, \ldots, m$), where $s$ is situational knowledge component, $N_i$ is the normative knowledge which includes information of interval and bound for the $i$th parameter, $N_i$ is represented as $N_i = (I_i, L_i, U_i)$. $I_i = [l_i, u_i]$ represents the closed interval of parameter $i$, where lower bound $l_i$ and upper bound $u_i$ are initialised as the given domain values and can be changed later. $L_i$ represents the performance score of the lower bound $l_i$ of parameter $i$. $U_i$ denotes the performance score of the upper bound $u_i$ for parameter $i$.

The acceptance function selects cultural sparks who can directly impact the formation of current belief space. In cultural FA the normative knowledge can be impacted by different cultural sparks. In this paper, the acceptance function selects the top 20% cultural sparks from $q$ locations.

The situational knowledge $s$ will be updated by the following updating function:

$$s^{t+1} = \begin{cases} x_{\text{best}}^t, & \text{if } f(x_{\text{best}}^t) < f(s^t) \\ s^t, & \text{otherwise} \end{cases}$$

where $x_{\text{best}}^t$ is the best spark location of cultural sparks population at the $t$th generation.

The normative knowledge $N$, will be updated by updating function. Assume now it is the $j$th cultural spark that affects the lower bound for parameter $i$, the lower boundary and its score are given below:

$$l_i^{t+1} = \begin{cases} x_i^j, & \text{if } x_i^j \leq l_i^t \text{ or } f(x_i^j) < l_i^t \\ l_i^t, & \text{otherwise} \end{cases}$$

$$l_i^{t+1} = \begin{cases} f(x_i^j), & \text{if } x_i^j \leq l_i^t \text{ or } f(x_i^j) < l_i^t \\ l_i^t, & \text{otherwise} \end{cases}$$

where $l_i^t$ represents lower bound for parameter $i$ at generation $t$ and $L_i^t$ denotes the performance score for it.

Assume now it is the $k$th cultural spark that impacts the upper bound for parameter $i$:

$$u_i^{t+1} = \begin{cases} x_i^k, & \text{if } x_i^k \geq u_i^t \text{ or } f(x_i^k) < U_i^t \\ u_i^t, & \text{otherwise} \end{cases}$$

$$U_i^{t+1} = \begin{cases} f(x_i^k), & \text{if } x_i^k \geq u_i^t \text{ or } f(x_i^k) < U_i^t \\ U_i^t, & \text{otherwise} \end{cases}$$

where $u_i^t$ represents upper bound for parameter $i$ at generation $t$ and $U_i^t$ denotes the performance score for it.
3.2 Evolution of CF algorithm

In this paper, we propose the use of fireworks as a population space of a CA. FA is a relatively recent intelligence algorithm that has been found to be robust as a search engine for real parameter optimisation. Adding cultural knowledge source to the variation operator of fireworks evolution, it is possible to improve the search and reduce the computational cost necessary to approximate the global optima of different optimisation problems.

When a CF is set off, a shower of sparks will fill the local space around the CF. The explosion process of a CF can be viewed as a search in the local space around a specific point where the CF is set off through the sparks generated in the explosion. When we are asked to find an optimal point, we can continually set off firework in potential space until one cultural spark is fairly near or attain the optimal point. In the CF, for each generation of explosion, we first select $p$ locations, where $p$ CFs are set off. Then after explosion, the locations of sparks are obtained and evaluated. When the optimal location is found, the algorithm stops. Otherwise, other $p$ locations are selected from the current cultural sparks and previous CFs for the next generation explosion.

At the beginning of explosion of each generation, $p$ locations should be selected for the CFs explosion. In the CF algorithm, the current top $\mu (0.05 < \mu < 0.5)$ locations of $q$ locations are always kept for the explosion. After that, $p - \mu q$ different locations are selected by their distance to other locations so as to keep diversity of cultural sparks. The general distance between a location $x_i = (x_{i1}, x_{i2}, ..., x_{in})$, $i \in \{\mu q + 1, \mu q + 2, ..., q\}$ and the other locations $x_j = (x_{j1}, x_{j2}, ..., x_{jn})$ is defined as follows:

$$R(x_i) = \sum_{j=\mu q+1}^{q} d(x_i, x_j) = \sum_{j=\mu q+1}^{q} \|x_i - x_j\| \quad (7)$$

Then the selection probability of a location $x_i$ is defined as follows:

$$v(x_i) = \frac{R(x_i)}{\sum_{j=\mu q+1}^{q} R(x_j)} \quad (8)$$

Through observing CFs display, we have given some specific behaviour of CFs explosion. When CFs are well manufactured, numerous cultural sparks are generated, and the cultural sparks centralise the explosion centre. In this case, we enjoy the spectacular display of the fireworks. However, for a bad firework explosion, quite a few cultural sparks are generated and cultural sparks scatter in the space.

From the search standpoint, a good CF denotes that the CF locates in a promising area which may be close to the optimal location. Thus, it is proper to utilise more cultural sparks to search the local area around the firework. In the contrast, a bad firework means the optimal location may be far from where the firework locates. Then, the search radius should be larger. In the CF, more sparks are generated and explosion amplitude is smaller for a good firework, compared to a bad one.

The number of sparks generated by each firework is defined as follows:

$$q_i = q \cdot \frac{y_{\max} - f(x_i)}{\sum_{i=1}^{q} (y_{\max} - f(x_i))} \quad (9)$$

where $q$ is a parameter controlling the total number of cultural sparks generated by the $p$ fireworks. $y_{\max} = \max\{|f(x)|, j = 1, 2, ..., q\}$ is maximum (worst) value of the objective function among the $q$ locations.

To avoid overwhelming effects of splendid fireworks and preserving diversity of CFs, the bound of fireworks number is defined by $\tilde{q}_i$, which is shown in the following equation:

$$\tilde{q}_i = \begin{cases} \text{round}(ap), & \text{if } q_i < ap; \\
\text{round}(bp), & \text{if } q_i > bp; \\
\text{round}(q_i), & \text{otherwise}
\end{cases} \quad (10)$$

where $a$ and $b$ are cost parameters. For satisfying the equation $\sum_{i=1}^{p} \tilde{q}_i = q$, $\tilde{q}_i$ may be slightly adjusted by deleting excellent fireworks or adding poor fireworks.

By changing the search size and direction of the variation with belief space, the cultural spark of CF $j$ is generated by:

$$x'_{ji} = \begin{cases} x_{ji} + \text{size}(I'_j) \cdot N(0,1), & \text{if } x_{ji} < l'_j; \\
-x_{ji} + \text{size}(I'_j) \cdot N(0,1), & \text{if } x_{ji} > u'_j; \\
-x_{ji} + \eta \cdot \text{size}(I'_j) \cdot N(0,1), & \text{otherwise}
\end{cases} \quad (11)$$

where $N(0,1)$ stands for the random number of standard normal distribution, size$(I'_j)$ stands for adjustable variable length of the belief space range at generation $t$, $\eta$ is a constant $(0.01 – 0.6)$ or a variant in a certain range.

By changing the search size and direction of the variation with belief space, the cultural spark of CF $j$ is generated by:

$$x'_{ji} = \begin{cases} x_{ji} + \text{size}(I'_j) \cdot N(0,1), & \text{if } x_{ji} < l'_j; \\
-x_{ji} + \text{size}(I'_j) \cdot N(0,1), & \text{if } x_{ji} > u'_j; \\
-x_{ji} + \eta \cdot \text{size}(I'_j) \cdot N(0,1), & \text{otherwise}
\end{cases} \quad (12)$$

To keep the diversity of sparks, we design other two-ways of generating cultural sparks location, which are defined as:
And the form of the frequency response is:

\[ EH(\omega) = \sum_{n=0}^{N-1} h[n]e^{-ijn} \]  

where \[ h[n] \] is the impulse which is \( h[n] \neq 0 \), the transfer function of the filter can be written as:

\[ H(z) = A_0 \prod_{k=1}^{N} \frac{1 + a_{k}z^{-1} + b_{k}Z^{-2}}{1 + c_{k}Z^{-1} + d_{k}Z^{-2}} \]  

So, the frequency response of the IIR filter is described as:

\[ H(e^{j\omega}) = A_0 \prod_{k=1}^{N} \frac{1 + a_{k}e^{j\omega} + b_{k}e^{2j\omega}}{1 + c_{k}e^{j\omega} + d_{k}e^{2j\omega}} = A_0 G(e^{j\omega}) \]

Under the assumption that ideal amplitude frequency characteristic is \( |H_d(e^{j\omega})| \), the optimum filter design is described as follows: minimum mean square error of IIR digital filter in frequency domain is carried out on discrete frequency points \( \{\omega_i | i = 1, 2, \ldots, M\} \) to make the mean square error between amplitude frequency of designed filter and that of ideal filter reach to minimum. The objective function of IIR filter can be written as:

\[ E_F = \sum_{i=1}^{M} \left[ |H_d(e^{j\omega})| - |H_d(e^{j\omega})| \right]^2 \]  

where \( F \) is number of frequency interval. From (17), we can rewrite the above equation as:

\[ E_F = \sum_{i=1}^{M} \left( \sum_{n=0}^{N-1} h[n]e^{j\omega_n} - |H_d(e^{j\omega})| \right)^2 \]  

The design problem of FIR filter is reduced to find out \( h(n) \) by minimising the squared error \( E_F \).

Transfer function of the IIR filter is described as:

\[ H(Z) = A_0 \prod_{k=1}^{N} \frac{1 + a_{k}Z^{-1} + b_{k}Z^{-2}}{1 + c_{k}Z^{-1} + d_{k}Z^{-2}} \]

4 Digital filters of FIR and IIR based on CF algorithm

4.1 Model of FIR and IIR digital filter

FIR filter has a finite number of non-zero entries of its impulse which is \( h[n] \), \( (n = 0, 1, \ldots, N-1) \). If we assume that \( h[n] \neq 0 \), the transfer function of the filter can be written as:

\[ H(z) = \sum_{n=0}^{N-1} h[n]z^{-n} \]

And the form of the frequency response is:

\[ H(e^{j\omega}) = \sum_{n=0}^{N-1} h[n]e^{-ijn} \]  

Consider the ideal frequency response \( H_d(e^{j\omega}) \) with the samples divided into equal frequency interval, we can get:

\[ H_d(e^{j\omega}) \bigg|_{\omega = \frac{2\pi}{N}} = H_d(k) \]  

where \( H_d(k) \) is regarded as the frequency response of the filter.

To design linear-phase FIR filter, we should minimise the error between the actual and ideal output. We define the error function as the error between the desired amplitude and the actual amplitude at a certain frequency, that is:

\[ E_F(e^{j\omega}) = H_d(e^{j\omega}) - H(e^{j\omega}) \]  

Thus, the objective of the total squared error in frequency domain is the minimisation of following function:

\[ E_F = \sum_{i=1}^{M} \left[ |H_d(e^{j\omega})| - |H(e^{j\omega})| \right]^2 \]  

where \( M \) is the number of frequency interval. From (17), we can rewrite the above equation as:

\[ E_F = \sum_{i=1}^{M} \left( \sum_{n=0}^{N-1} h[n]e^{j\omega_n} - |H_d(e^{j\omega})| \right)^2 \]  

So, the frequency response of the IIR filter is described as:

\[ H(e^{j\omega}) = A_0 \prod_{k=1}^{N} \frac{1 + a_{k}e^{j\omega} + b_{k}e^{2j\omega}}{1 + c_{k}e^{j\omega} + d_{k}e^{2j\omega}} = A_0 G(e^{j\omega}) \]
4.2 Objective function of FIR and IIR digital filter

According to the above discussion, design of digital filters based on the intelligence algorithm may be written as:

\[
\hat{x} = \arg\min_x [\alpha E_F + \beta E_I]
\]  

(26)

where \(x = [h(0), \ldots, h(N-1)]\) or \(x = [a_0, b_0, c_0, d_0, \ldots, a_N, b_N, c_N, d_N]\), \(\alpha + \beta = 1\), \(\alpha \in \{0, 1\}\), \(\beta \in \{0, 1\}\). We can design FIR digital filter with \(\alpha = 1\) and IIR digital filter with \(\beta = 1\). For digital filters design of the constraint condition, \(\hat{x} \in s.t\) also should satisfy design requirement.

4.3 Digital filter based on CF algorithm

The goal of the fitness function is to evaluate the status of each CF. In the FIR and IIR digital filter design based on cultural FA, the optimisation target of firework location is the minimisation of the following objective function:

\[
f(x) = \begin{cases} 
\alpha E_F + \beta E_I & \text{if } x \in s.t \\
\delta \left(\alpha E_F + \beta E_I\right) & \text{if } x \notin s.t
\end{cases}
\]  

(27)

where \(s.t\) denotes the constraint condition of vector \(x\) and \(\delta\) is positive constant which is limited to \(\delta > 1\).

The procedure for implementing of CF algorithm is given by the following steps:

Step 1  According to design requirement, select values of \(\alpha\), \(\beta\) and \(\delta\), where \(\delta\) is equal to 0 for a non-constraint problem.

Step 2  Randomly select an initial population of the \(q\) candidate solutions within the given domains, and initialise belief space.

Step 3  Evaluate the performance scores of population space by a given objective function.

Step 4  Select the \(p\) initial locations from the \(q\) locations.

Step 5  Set off cultural fireworks at the \(p\) locations. According to the designed influence function, \(q\) spark locations of CFs are presented by (11), (12), (13) and (14) with certain probability.

Step 6  Calculate objective functions of the new locations.

Step 7  Select the top \(q\) different locations from the \(2q\) cultural sparks which include the cultural sparks of current and parent generation for the next generation (iteration).

Step 8  According to the acceptance function to select excellent locations, belief space is updated by equations (2) to (6).

Step 9  If it has not met the termination condition (the termination condition is set as maximum iteration times in generally), then back to Step 4; else the algorithm stops.

5 Evaluation and experimental results

We employed PSO (Li et al., 2006), quantum-behaved PSO (QPSO) (Fang et al., 2006) and adaptive QPSO (AQPSO) (Fang et al., 2008) to design the digital filters for the performance comparison with filter based on the proposed CF algorithm (CF algorithm is simply written as CF in this section). In each running of the CF, the PSO, the QPSO and the AQPSO, population size of all intelligence algorithms is set to 100 and initial individuals of intelligence algorithms are identical for convenient of comparison. In CF, some parameters are set as: \(\mu = 0.3\), \(\eta \in 0.06–0.1\), \(p = 40\), \(a = 0.025\), \(b = 0.2\), \(c = 1\), \(A_j = 0.3 \cdot p\).

5.1 Simulation of FIR filter design

The examples of FIR digital filter design are a low-pass filter and a band-pass filter. Their frequency responses are designed as follows:

\[
H_d(e^{j\omega}) = \begin{cases} 
1, & 0 \leq \omega \leq 0.2\pi; \\
0, & 0.3\pi \leq \omega \leq \pi
\end{cases}
\]  

(28)

\[
H_d(e^{j\omega}) = \begin{cases} 
1, & \omega_{h_1} \leq \omega \leq \omega_{h_2}; \\
0, & 0 \leq \omega \leq \omega_{h_1}, \omega_{h_2} \leq \omega \leq \pi.
\end{cases}
\]  

(29)

where \(\omega_{h_1} = 0.23\pi\), \(\omega_{h_2} = 0.33\pi\), \(\omega_2 = 0.67\pi\), \(\omega_{h_2} = 0.77\pi\).

The search scope of the coefficient of the FIR digital filter is set as \([-1, 1]\). The number of frequency interval is set as \(N = 30\). The responses of transition-band are selected as 0.5941 and 0.109021 by the method of look-up table.

Figure 1  Convergence behaviours of low-pass FIR filter
Figure 2  Convergence behaviours of band-pass FIR filter

![Convergence behaviours of band-pass FIR filter](image)

Table 1  Comparison of four-algorithms for FIR filter

<table>
<thead>
<tr>
<th></th>
<th>Low-pass filter</th>
<th>Band-pass filter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PSO</td>
<td>QPSO</td>
</tr>
<tr>
<td>max</td>
<td>1.8505e-3</td>
<td>8.8845e-9</td>
</tr>
<tr>
<td>min</td>
<td>7.5908e-5</td>
<td>6.6311e-12</td>
</tr>
<tr>
<td>mean</td>
<td>3.9566e-4</td>
<td>5.8634e-10</td>
</tr>
<tr>
<td>var</td>
<td>8.6053e-8</td>
<td>1.3445e-18</td>
</tr>
</tbody>
</table>

Figure 3  Amplitude response of low-pass FIR filters

![Amplitude response of low-pass FIR filters](image)

Figure 4  Amplitude response of band-pass FIR filters

![Amplitude response of band-pass FIR filters](image)

Figure 1 and Figure 2 show the comparison of convergence behaviour of FIR low-pass and band-pass filters designed by four-algorithms with 100-trial runs. From the generated results in Figure 1 and Figure 2, it can be concluded that the CF works better than the other three-algorithms with more rapid convergence speed. Simulation data may obtain from Table 1 where ‘max’ denotes maximal value of objective function, ‘min’ denotes minimal value of objective function, ‘mean’ denotes mean value of objective function, ‘var’ denotes variance value of objective function with 100-trial runs.

Figure 3 and Figure 4 show the comparison of amplitude response of FIR low-pass and band-pass filters designed by four different algorithms with 230-iterations. From the simulation results in Figure 3 and Figure 4, it can be seen that with the same iterations, the CF is superior to the PSO, the QPSO and the AQPSO algorithm.

5.2 Simulation of IIR filter design

The example of IIR filter design is a high-pass filter. Its frequency response is written as:

$$H_d(e^{j\omega}) = \begin{cases} 1, & 0.47\pi \leq \omega \leq \pi; \\ 0, & 0 \leq \omega \leq 0.4\pi \end{cases}$$  \hspace{1cm} (30)

The search scopes of the coefficient of the filter are set as [-2, 2] and [-1, 1] for different parameters. Parameter dimension of intelligence algorithms for IIR digital filter is 12. The responses of transition-band are selected as 0.5941 and 0.109021 by the method of look-up table.
Cultural firework algorithm and its application for digital filters design

To show the difference of IIR high-pass filter designed by different algorithms, we provide simulations with 100-trial runs in Figure 5. From the simulation results of the three-filters, it can be concluded that the CF works better than the other two-algorithms with more rapid convergence speed. Simulation data may obtain from Table 2. It is obvious that the CF is an excellent algorithm to design FIR and IIR digital filters. The CF is superior to the QPSO and the AQPSO in maximal value, minimal value, mean value and variance value of objective function with 100-trial runs.

Table 2 Performance comparison of IIR filters

<table>
<thead>
<tr>
<th>Objective value</th>
<th>High-pass filter</th>
<th>QPSO</th>
<th>AQPSO</th>
<th>CF</th>
</tr>
</thead>
<tbody>
<tr>
<td>max</td>
<td>1.0696e-1</td>
<td>1.7308e-1</td>
<td>9.5554e-2</td>
<td></td>
</tr>
<tr>
<td>min</td>
<td>3.6419e-3</td>
<td>3.6608e-3</td>
<td>1.0059e-3</td>
<td></td>
</tr>
<tr>
<td>var</td>
<td>1.0942e-3</td>
<td>3.8210e-3</td>
<td>9.9703e-4</td>
<td></td>
</tr>
</tbody>
</table>

Figure 6 shows the comparison of amplitude response of IIR high-pass filter by three-algorithms with 400-iterations. It can be seen that with the same iterations number, the CF works better than the QPSO and the AQPSO algorithm.

5.3 Simulation of FIR filter with constraint condition

We need design low-pass and band-pass FIR filters that passband ripples are respectively 0.25 dB and 0.36 dB. In CF, δ is set as 10. In the QPSO and the AQPSO, the constraint condition isn’t considered with previous objective function (Gao et al., 2008). Table 3 shows the performance comparison of FIR low-pass and band-pass filters designed by four-algorithms with 100-trial runs and 400-iterations. The CF can satisfy the constraint condition with 100-trial runs and stopband attenuation also is optimal. Other three-algorithms cannot satisfy the limited condition in the most case. So, the proposed objective function of filter design is efficient.

As shown in the experiments the CF has a faster convergence speed and better optimisation accuracy. Compared the PSO, the QPSO and the AQPSO algorithm, we consider that the advantages of the CF lie in the following aspects. Four types of cultural spark operators are designed to keep the diversity of cultural sparks, and selection process for locations is a mechanism for keeping diversity. Therefore, the CF has the capability of avoiding premature convergence.

Table 3 Performance comparison of FIR filters

<table>
<thead>
<tr>
<th>Performance</th>
<th>Low-pass filter</th>
<th>Band-pass filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>QPSO</td>
<td>AQPSO</td>
</tr>
<tr>
<td>-----------------</td>
<td>------</td>
<td>-------</td>
</tr>
<tr>
<td>Passband ripple (dB)</td>
<td>0.2343</td>
<td>0.30632</td>
</tr>
<tr>
<td>Success probability</td>
<td>10%</td>
<td>0</td>
</tr>
<tr>
<td>Stopband attenuation (dB)</td>
<td>-39.473</td>
<td>-64.489</td>
</tr>
</tbody>
</table>

6 Conclusions and future works

In this paper, CF algorithm, a novel fireworks population-based search technique is proposed for the design of FIR and IIR filters. The CF algorithm is able to converge to the near global optima with less time consumption and seems to outperform the QPSO, the AQPSO and the original PSO algorithm. From the experiment results on FIR filter and IIR filter design, we can...
conclude that cultural FA provides an efficient and alternative approach for digital filter design. In the future, we will explore the applicability of cultural FA for other optimal problems.

Acknowledgements
This work is supported by the Fundamental Research Funds for the Central Universities, No. HEUCF100801.

References