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Published in IET Signal Processing
Received on 1st August 2010
Revised on 22nd March 2012
doi: 10.1049/iet-spr.2011.0092

ISSN 1751-9675

Non-linear active noise cancellation using a bacterial foraging optimisation algorithm

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Abstract: This study presents a new scheme for non-linear active noise control (ANC) systems. In the proposed ANC system, a new evolutionary algorithm known as bacterial foraging (BF) is used for optimising the adaptive controller. The proposed ANC system using bacterial foraging optimisation (BFO) has the ability to prevent falling into local minima. Moreover, using the BF algorithm to adapt the ANC filter coefficients removes the need for the preliminary identification of the secondary path**.** Several computer simulations are developed in order to analyse the performance of the proposed BFO-based ANC system (BFO-ANC). The experiments are carried out in two major groups including a linear and a non-linear secondary path, along with a non-linear primary path. In each group, the effect of different parameters of the BFO algorithm is investigated on the performance and robustness of the proposed ANC system. The authors also compare the results obtained by three ANC systems; the proposed BFO-based ANC, the GA-based ANC and the filtered-X LMS-based ANC. Simulation results demonstrate the effectiveness of the proposed BFO method in noise cancellation performance under several situations.

1 Introduction

Active noise control (ANC) systems have received much attention in recent research and industrial applications. Compared with passive noise cancellation techniques using passive absorbers, ANC has the advantage of being able to suppress an acoustic noise at low frequency with much smaller size, weight, volume and cost. The design of an ANC system is based on the principle of destructive interference between the original noise source and a secondary source with the same amplitude and opposite phase. The secondary source is produced by an adaptive controller [1–3]. Most of the studies presented in the literature refer to linear models of ANC systems. However, a linear model usually does not perform well in the cases where non-linear phenomena occur. These non-linear situations involve the non-linearities present in the noise source and the acoustic paths [4–8].

The filtered-X LMS algorithm is usually used as an algorithm to update the adaptive filter coefficients. Although this algorithm has less computational complexity for active control of input noise, it has several limitations. For instance, it may converge to a local minimum during the adaptation process, in cases such as a non-linear secondary path. It also requires the preliminary identification of the secondary path [9–11]. To overcome such limitations of LMS-based algorithms, soft computing approaches have been successfully employed in many researches [12–15]. These methods include the fuzzy filtered-X algorithm presented in [12] and the neural network strategies proposed in [13–15]. Researches in [16–18] have utilised the Volterra-based methods in ANC systems. However, these methods must still identify the secondary path in advance. This requirement may pose many problems. Some of these problems are the possible divergence of the adaptation algorithms owing to the identification errors, increasing the residual error when online identification is used and increasing the computational complexity. In this respect, a control algorithm that does not explicitly require the identification of the secondary path may alleviate these problems.

Most approaches in the literature are based on the LMS algorithms whereas only a few techniques resorted to evolutionary algorithms. Researchers in [19–21] applied the genetic algorithm (GA) to adapt the coefficients of finite impulse response (FIR) and infinite impulse response (IIR) linear filters. Russo and Chang presented a genetic optimisation scheme for several linear and non-linear systems. This class of algorithms does not require identifying the secondary path. However, in these methods, a large size of population for many generations is needed to reach a high level of noise cancellation.

A new algorithm from the family of evolutionary computation, known as BF algorithm, has been recently proposed [22, 23]. Owing to its biological motivation and graceful structure, this algorithm has drawn the attention of many researchers from diverse fields of knowledge [24–28]. The algorithm is based on the foraging behaviour of *Escherichia coli* (*E. coli*) bacteria present in human intestine. Bacteria search for nutrients in order to maximise the energy obtained per unit time. They undergo different stages such as chemotaxis, swarming, reproduction and elimination-and-dispersal.

In this paper, the BFO algorithm, for the first time, is employed to adjust the adaptive controller in an ANC system. An adaptive Volterra filter is also used as the non-linear controller to handle the non-linear effects of the acoustic systems. The coefficients of the adaptive controller are optimised as the control variables. The rest of the paper is organised as follows. Section 2 provides a brief overview of the BF algorithm. The proposed non-linear ANC system using the BFO algorithm is presented in Section 3. Section 4 presents the results of computer simulations and finally, Section 5 concludes the paper.

2 BFO algorithm

A new evolutionary computation technique, called the BFO scheme, has recently been introduced [22, 23]. The idea of BFO is based on the fact that natural selection tends to eliminate animals with poor foraging strategies and favours those having successful foraging strategies. After many generations, poor foraging strategies are either eliminated or reshaped into good ones. The *E. coli* bacteria that are present in human intestine have a foraging strategy governed by four processes, namely, chemotaxis, swarming, reproduction and elimination-and-dispersal.

1. *Chemotaxis:* This process is achieved through swimming and tumbling. Depending upon the rotation of the flagella, the bacterium decides in what direction it should move, which is called tumbling. If the new location of the bacterium after moving gets better, the bacterium begins to swim in the same previous direction, called swimming. To represent a tumble, a unit length random direction is generated. This unit length is used to define the direction of movement after a tumble.
2. *Swarming:* It is always desired that the bacterium that has searched the optimum path of food should try to attract other bacteria so that they reach the desired place more rapidly. Swarming makes the bacteria congregate into groups and hence move as a concentric pattern of groups with high bacterial density.
3. *Reproduction:* Half of the bacteria that are less healthy die. Each of the other healthier bacteria splits into two bacteria, at their own location. This makes the population of bacteria constant.
4. *Elimination and Dispersal:* It is possible that in the local environment, the lives of a population of bacteria change either gradually by consumption of nutrients or suddenly owing to some other influence. Events can occur such that all the bacteria in a region are killed or a group is dispersed into a new part of the environment. They have the effect of possibly destroying the chemotactic progress, but they also have the effect of assisting in chemotaxis, since dispersal may place bacteria at better locations. Elimination and dispersal prevents bacteria from being trapped in local optima [22].

3 Proposed non-linear ANC system using BF algorithm

In this section the BFO algorithm has been employed to optimise the adaptive filter coefficients in an ANC system, called BFO-ANC. The block diagram of the proposed system is shown in Fig. 1. In this figure, $x(n)$ is the noise sensed by a reference microphone. The primary path, $P(z)$, consists of the acoustic response from the noise source to the cancelling point. The signal at the location where the noise has to be attenuated is denoted by $d_p(n)$.

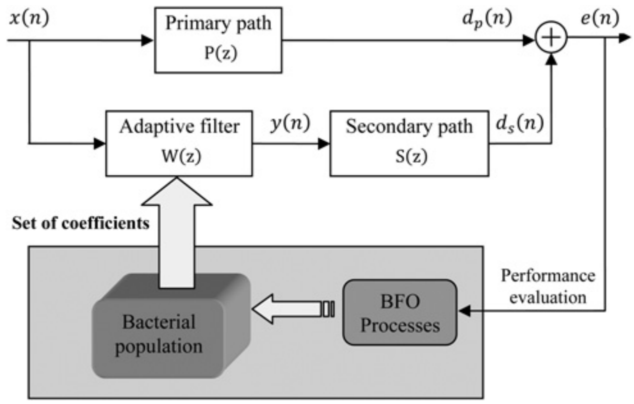

Fig. 1 *Block diagram of the proposed non-linear BFO-ANC*

The reference microphone collects the samples of the noise source and feeds them as input to the adaptive controller. The signal generated by the adaptive controller is denoted by $y(n)$. This signal drives the secondary source to produce the secondary cancelling signal $d_s(n)$.

This is the interfering signal received at the same location where an error microphone collects the error signal, given by

$$e(n) = d_p(n) + d_s(n) \quad (1)$$

This signal is used as the performance index to evaluate the BF optimisation procedure. In order to use the BFO in an ANC process, a set of coefficients of the adaptive filter is assumed as a bacterium. The length of coefficients array shows the number of parameters in a bacterium, which indicates the dimension of optimisation space.

In this paper, the BF algorithm is modified to reduce the computational complexity and expedite the convergence. The two modifications are as follows:

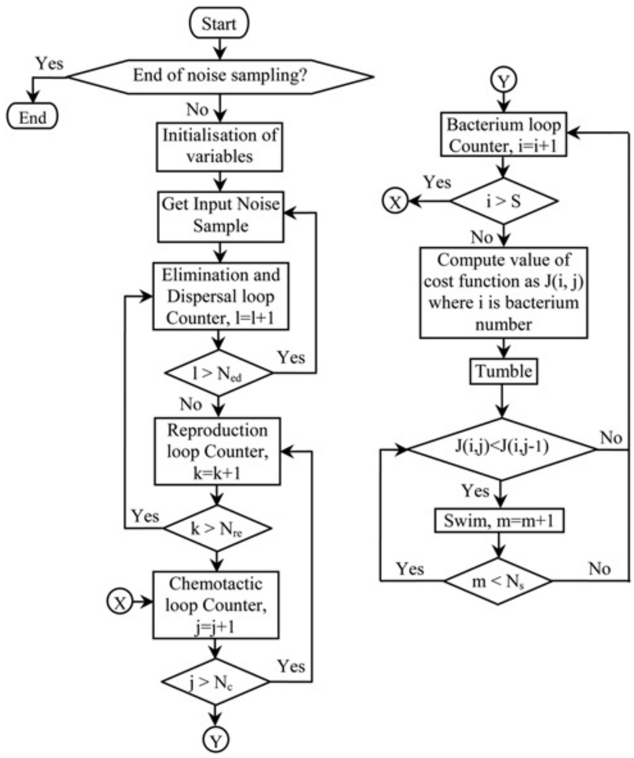

Fig. 2 *Flowchart of the proposed BFO-ANC*

1. The minimum value of all the chemotactic cost functions is retained to decide the bacterium's health.
2. The cell-to-cell attractant function is ignored in swarming, to reduce the complexity.

The proposed algorithm for the BFO-ANC system has three main steps as follows:

Step 1: Initialisation of the parameters.
Step 2: Get the incoming noise samples: For each noise sample the algorithm runs separately and the corresponding residual noise is obtained.
Step 3: Run the iterative algorithm for optimisation: This step models the bacterial population chemotaxis, reproduction and elimination and.dispersal.

The detailed description of the proposed algorithm is presented in Appendix 1. The flowchart of the described algorithm is shown in Fig. 2.

4 Simulation results

In order to analyse the performance of the proposed ANC system using BF optimisation, several experiments are performed. The results of these simulations are shown in this section. In these experiments, the primary path has been modelled as a cascade of a linear filter and a non-linear one [10, 18]. The linear filter is defined by

$$s(n) = x(n-5) - 0.3x(n-6) + 0.2x(n-7) \qquad (2)$$

The non-linear filter is defined by the following third-order polynomial model

$$d_p(n) = s(n-2) + 0.08[s(n-2)]^2 - 0.04[s(n-2)]^3 \qquad (3)$$

The term $d_p(n)$ denotes the primary noise at the location where the noise has to be attenuated. It is recently reported that the noise generated by a dynamic system can be modelled as a non-linear and deterministic process of chaotic nature, rather than stochastic [10]. A logistic noise signal is used as the input noise. A chaotic logistic map is generated by the following expression

$$x(n+1) = \lambda x(n)[1 - x(n)] \;\text{ for }\; \lambda = 4 \,\text{and}\, x(0) = 0.9 \qquad (4)$$

A 20-coefficient Volterra filter is used as the adaptive

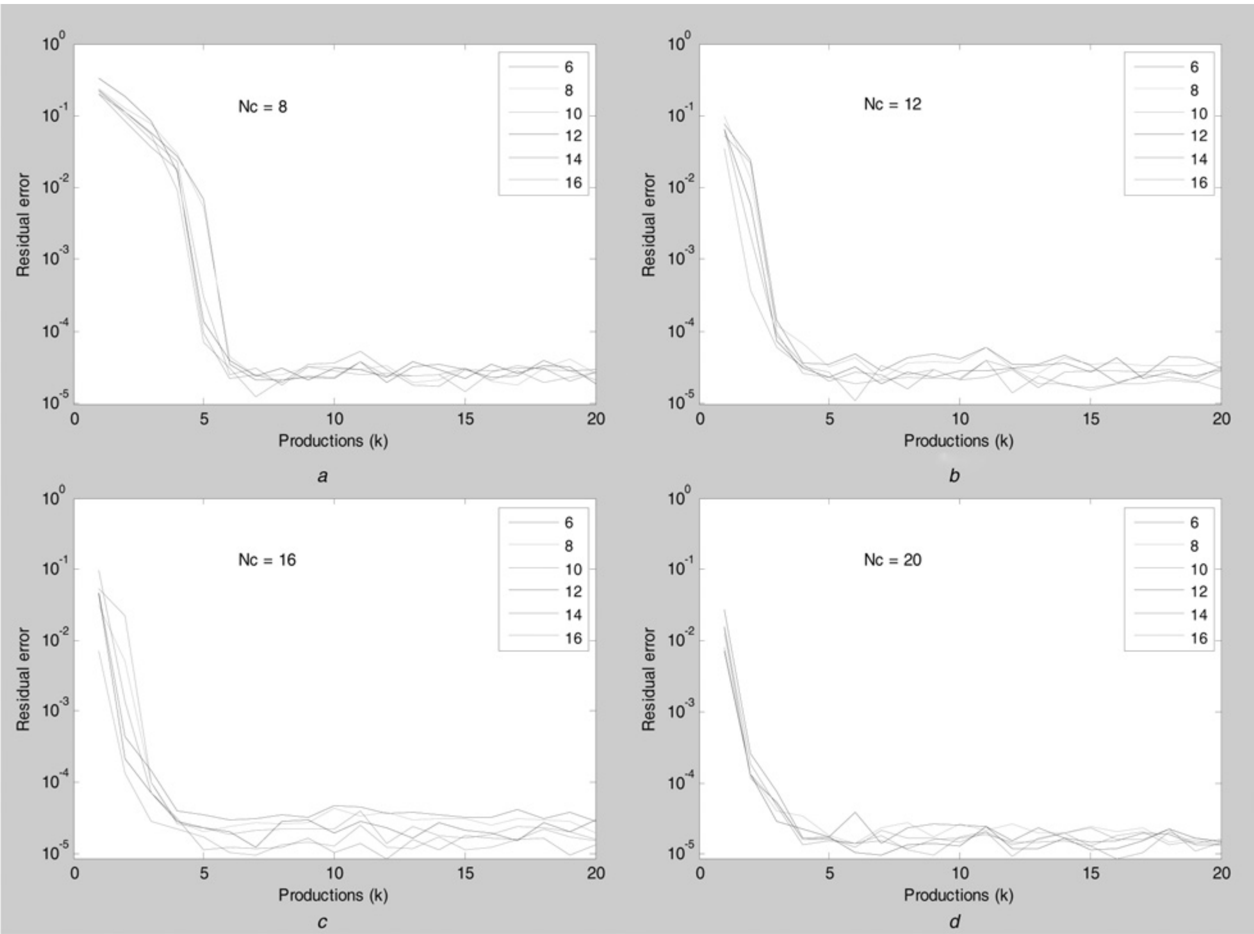

Fig. 3 *Case I (non-linear primary path and linear secondary path)*

Convergence characteristic of the BFO-ANC
a $N_c = 8$
b $N_c = 12$
c $N_c = 16$
d $N_c = 20$
Number of bacteria ranging from 6 to 16

doi: 10.1049/iet-spr.2011.0092

Table 1 Minimum cost function values for 20 reproduction steps

Number of bacteria (S)	Chemotactic iterations $N_c = 8$	Chemotactic iterations $N_c = 12$	Chemotactic iterations $N_c = 16$	Chemotactic iterations $N_c = 20$
6	3.24×10^{-5}	2.92×10^{-5}	2.67×10^{-5}	2.23×10^{-5}
8	2.98×10^{-5}	2.73×10^{-5}	2.41×10^{-5}	2.05×10^{-5}
10	2.76×10^{-5}	2.55×10^{-5}	2.12×10^{-5}	1.81×10^{-5}
12	2.58×10^{-5}	2.23×10^{-5}	1.91×10^{-5}	1.52×10^{-5}
14	2.31×10^{-5}	1.95×10^{-5}	1.74×10^{-5}	1.23×10^{-5}
16	2.09×10^{-5}	1.78×10^{-5}	1.53×10^{-5}	0.91×10^{-5}

non-linear filter defined by

$$y(n) = \sum_{i=0}^{9} h_i x(n-i) + \sum_{i=0}^{9} h_{i+10} x^2(n-i) \qquad (5)$$

The set of 20-coefficients of the Volterra filter h_i ($i = 0, 1, \ldots, 19$) is adapted by means of the BFO algorithm. One of the challenges in using the BFO algorithm is the appropriate selection of its parameters including S, N_c and N_{re}. The speed of convergence changes for different combinations of the above parameters. In this paper, we investigate the effect of these parameters on the convergence behaviour of the residual error. Two main groups of experiments, including linear and non-linear secondary path, are considered.

4.1 Case 1 – linear secondary path

In the first group of experiments, the secondary path is modelled by a linear filter of (6), given in [10, 18]

$$S_{\text{linear}}(z) = z^{-2} + 1.5z^{-3} - z^{-4} \qquad (6)$$

The performance and robustness of the proposed ANC system are investigated, using different choices of BFO parameters;

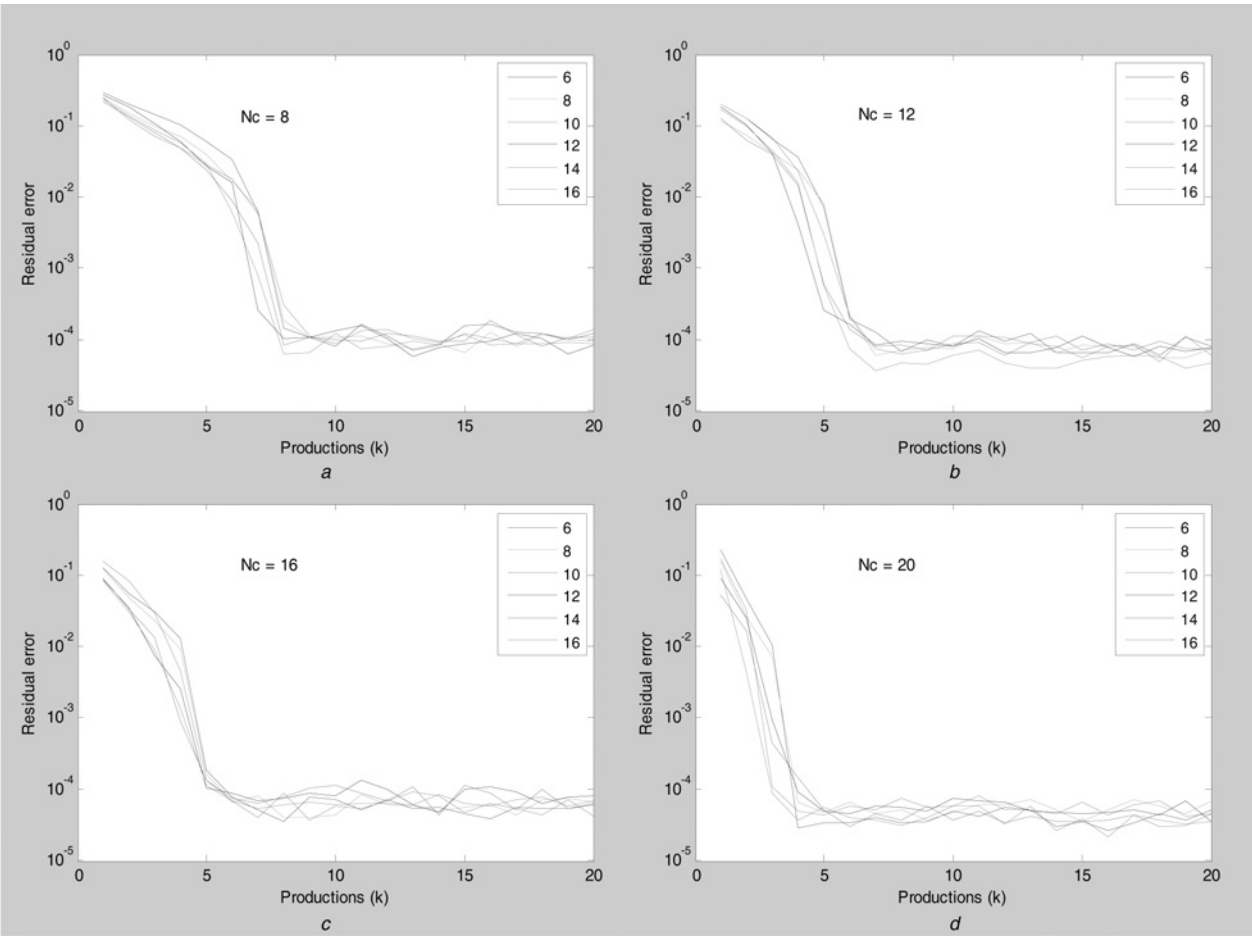

Fig. 4 *Case II (non-linear primary path and non-linear secondary path)*

Convergence characteristic of the BFO-ANC
a $N_c = 8$
b $N_c = 12$
c $N_c = 16$
d $N_c = 20$
Number of bacteria ranging from 6 to 16

Table 2 Minimum cost function values for 20 reproduction steps

Number of bacteria (S)	Chemotactic iterations $N_c = 8$	Chemotactic iterations $N_c = 12$	Chemotactic iterations $N_c = 16$	Chemotactic iterations $N_c = 20$
6	1.42×10^{-4}	1.25×10^{-4}	1.12×10^{-4}	1.04×10^{-4}
8	1.23×10^{-4}	1.12×10^{-4}	1.05×10^{-4}	0.85×10^{-4}
10	1.11×10^{-4}	0.97×10^{-4}	0.93×10^{-4}	0.55×10^{-4}
12	0.92×10^{-4}	0.85×10^{-4}	0.78×10^{-4}	0.46×10^{-4}
14	0.81×10^{-4}	0.79×10^{-4}	0.62×10^{-4}	0.25×10^{-4}
16	0.72×10^{-4}	0.68×10^{-4}	0.53×10^{-4}	0.19×10^{-4}

including the number of bacteria in the colony ranging from 6 to 16 and the number of iterations in a chemotactic loop ranging from 8 to 20. The input signal to the ANC system is considered to be a logistic chaotic noise, (4). The results of the computer simulations are shown in Figs. 3*a*–*d*, where the data are obtained by averaging on 100 input noise samples. As shown in these figures, increasing the chemotactic loop iterations, N_c, increases the convergence speed of the output residual error; whereas increasing the number of bacteria in the colony, S, decreases the value of the cost function. For the sake of clarity, the minimum residual error values obtained in each run are listed in Table 1.

4.2 Case 2 – non-linear secondary path

In the second group of experiments, the secondary path is modelled by a cascade of a non-linear filter and a linear one [10, 18]. The non-linear filter is given by

$$r(n) = 0.66\ \tanh(1.5y(n)) \tag{7}$$

The term $y(n)$ denotes the output of the adaptive controller. The secondary cancelling signal $d_s(n)$ is obtained by the following linear filter

$$d_s(n) = r(n-2) + 1.5r(n-3) - r(n-4) \tag{8}$$

Simulations are performed with the number of bacteria ranging from 6 to 16 and the chemotactic loop iterations ranging from 8 to 20, similar to the first experiment. The input signal to the ANC system is considered to be a logistic chaotic noise, (4). The results of the computer simulations are shown in Figs. 4*a*–*d*. The minimum residual error values are listed in Table 2.

Fig. 5 shows the cost function, considering $N_{re} = 20$ and $N_{ed} = 2$. As a result, 20 iterations complete one elimination-and-dispersal loop. The effect of the elimination-and-dispersal event is considered in this figure. Figs. 6*a* and *b* show the cost function and the computational time against the number of reproductions, N_{re}. These results are obtained with the mentioned initial values of all the parameters. As shown in this figure, increasing the number of reproductions (N_{re}) reduces the residual error a little, and increases the required time a lot. For example, increasing the number of reproductions from 10 to 20 decreases the cost function for 0.002%, whereas, it increases the required computational time for 23.68%.

Fig. 7 shows the simulation results of the bacteria motion trajectories over the optimisation domain for one input noise sample. The algorithm parameters are chosen as; $S = 4$, $N_c = 16$, $N_{re} = 11$, $N_{ed} = 1$. For better visibility, only 6, out of the 20 parameters of bacteria are shown. In each generation, the least healthy bacteria die and each of the other healthier bacteria splits into two bacteria, which are placed in the same location. The same colours in each figure correspond to the identical parameters in all of the bacteria.

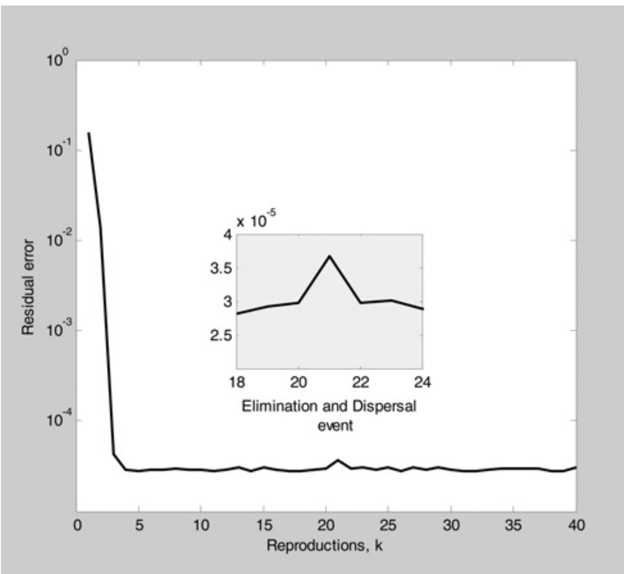

Fig. 5 *Convergence behaviour of the output residual error of BFO-ANC ($N_{re} = 20$, $N_{ed} = 2$)*

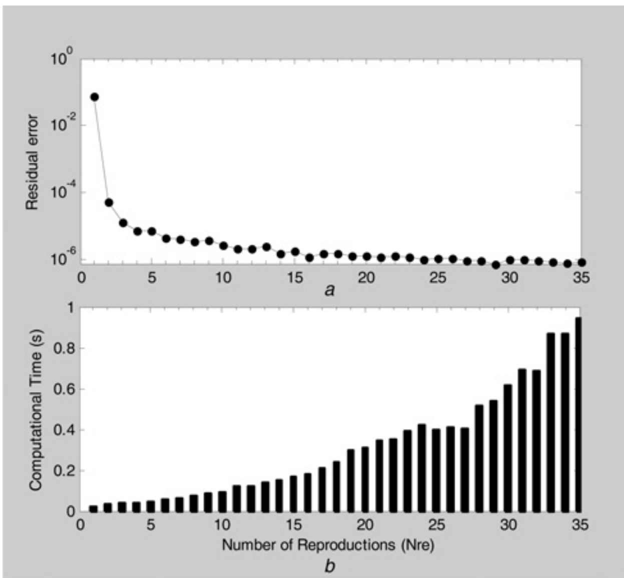

Fig. 6 *Residual error and the computational time*

a Residual error
b Computational time

doi: 10.1049/iet-spr.2011.0092

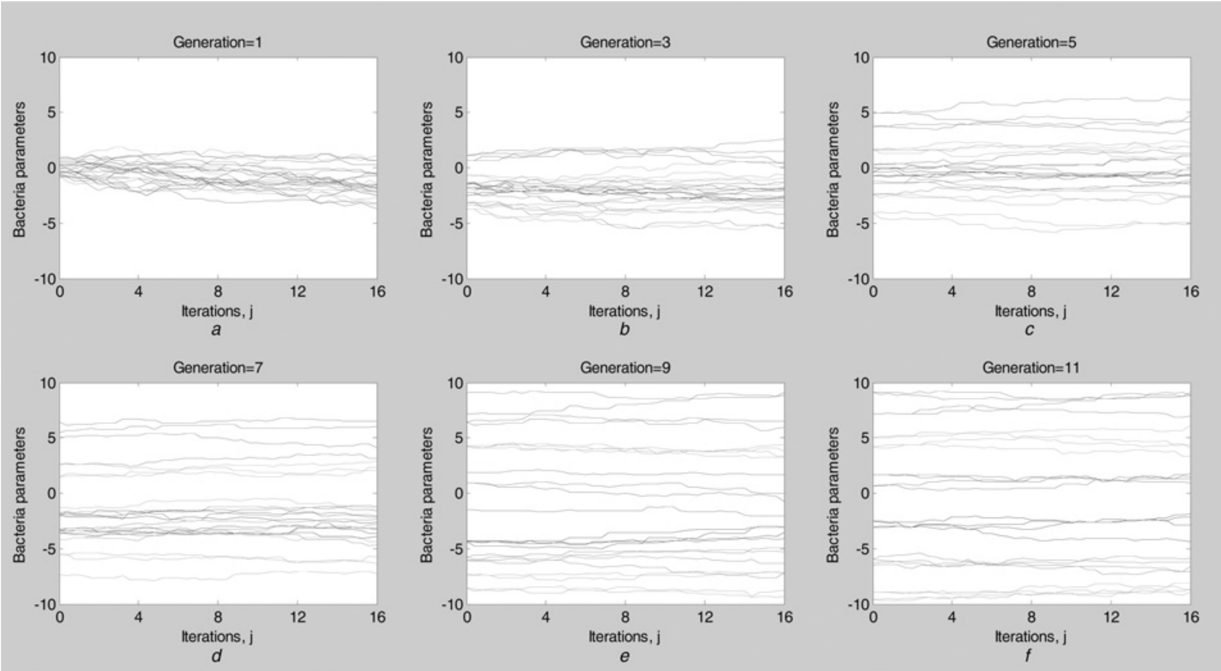

Fig. 7 *Bacteria motion trajectories*

a Generation 1
b Generation 3
c Generation 5
d Generation 7
e Generation 9
f Generation 11

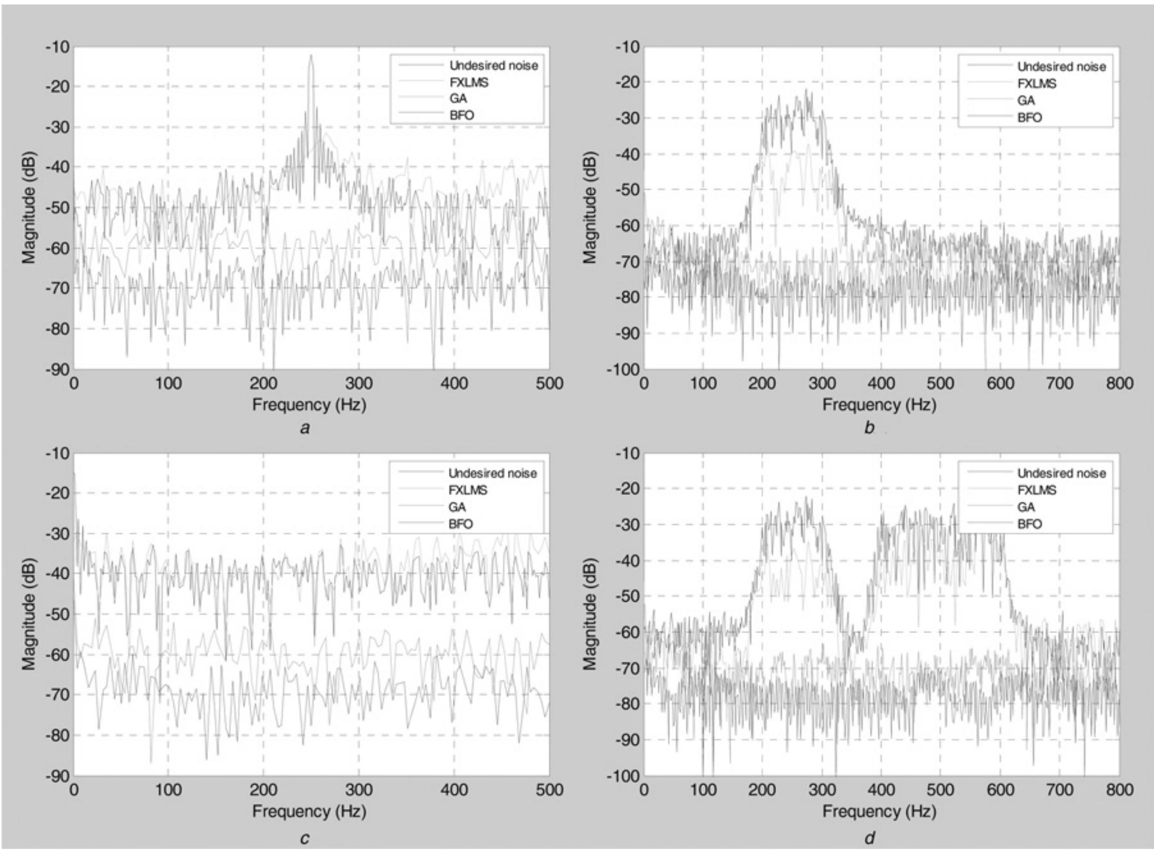

Fig. 8 *Noise cancellation performance for different ANC systems with a non-linear primary path and a linear secondary path*

a 250-Hz narrowband noise
b 200–300 Hz random noise
c Chaotic noise
d Two-frequency-band random noise

Table 3 Noise reduction performance of different ANC systems

Systems	Narrow band noise, dB	Random noise, dB	Chaotic noise, dB	Two-frequency-band random noise, dB
ANC with F-X LMS	−20.89	−15.88	−06.94	−11.25
ANC with GA	−43.78	−37.26	−19.76	−29.91
ANC with BFO (proposed)	−52.16	−44.68	−27.48	−34.21

In the next experiment, we compare the results obtained by the proposed BFO-ANC with those yielded by the GA ANC system investigated in [10] and the ANC using the standard filtered-X LMS algorithm. The parameter settings for the GA ANC systems and the F-X LMS-based ANC are considered to be the same as the settings proposed in [10] to have a fair comparison between the noise cancellation systems.

In this comparison, four types of input noise including a 250-Hz narrowband noise, a chaotic noise, a 200–300 Hz random noise and a two-frequency-band random noise (with frequencies ranging from 200 to 300 Hz and 400 to 600 Hz) are considered. This situation is considered because the most industrial noise has its main frequency within ranges of 200–300 and 400–600 Hz [11].

Two main groups of simulations including linear and non-linear secondary path are considered. The performance of cancelling out the input noise is presented in these simulations. In each figure, the original input noise (inputted noise to the ANC system) and the residual noises at the cancellation point (error microphone output) after applying different ANC systems are shown.

Fig. 8 shows the results obtained by the proposed BFO-ANC, GA ANC and the FXLMS-based ANC system for a non-linear primary path and linear secondary path. In our system, for the BFO algorithm, we consider $S = 12$, $p = 20$, $N_c = 16$, $N_s = 4$, $N_{re} = 10$, $N_{ed} = 2$, $C(i) = 0.1$, $P_{ed} = 0.25$ and the location of each bacterium, $P(1 - p, 1 - S, 1)$ is specified by a random number in the range of $[-1, 1]$.

For the GA ANC system and the F-X LMS-based ANC system, we use the settings proposed in [10]. The set of 20 coefficients of the non-linear Volterra filter are encoded as a 160 bit binary string. This parameter set is adapted by means of the GA with a population of 600 individuals. The crossover and mutation probabilities are set to 0.08 and 0.02, respectively; and the number of generations is set to 500. In the ANC system based on conventional F-X LMS algorithm, the step size is considered to be $\mu = 0.01$.

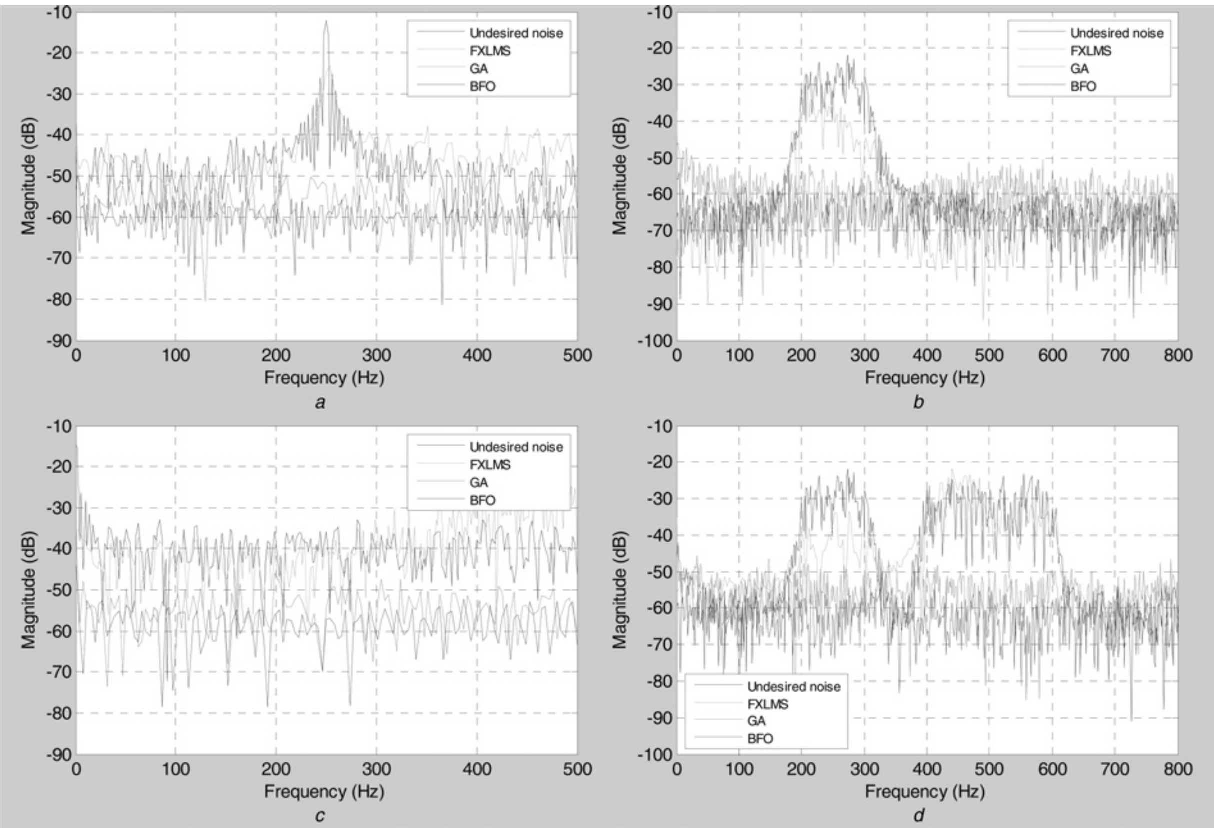

Fig. 9 *Noise cancellation performance for different ANC systems with a non-linear primary path and a non-linear secondary path*

a 250-Hz narrowband noise
b 200–30 Hz random noise
c Chaotic noise
d Two-frequency-band random noise

doi: 10.1049/iet-spr.2011.0092

Table 4 Noise reduction performance of different ANC systems

Systems	Narrow band noise, dB	Random noise, dB	Chaotic noise, dB	Two-frequency-band random noise, dB
ANC with F-X LMS	−15.76	−10.24	−04.91	−07.69
ANC with GA	−40.39	−32.88	−14.52	−24.05
ANC with BFO (proposed)	−47.84	−38.44	−21.58	−29.47

Analytical results are implemented by a personal computer with dual 2.5-GHz central processing units and 3-GB dynamic random access memory. The BFO algorithm involving 20 reproduction steps ($N_{re} \times N_{ed} = 20$), requires 8.2 s to be completed. The noise reduction values of each method for different kinds of input noise are listed in Table 3. The data have been obtained by averaging on 100 independent realisations. As shown in this table, our proposed BFO-ANC system has noise reduction of about 60% in comparison to the F-X LMS-based ANC and about 20% in comparison to the GA-based ANC. The noise reduction results for a non-linear primary path and non-linear secondary path are shown in Fig. 9. The values of noise reduction by averaging on 100 independent realisations are listed in Table 4. This table also shows the improvement of the proposed BFO-ANC system compared with the other two systems. Indeed, we can reach to a higher degree of noise reduction at the cost of more computing effort that leads to more consumption of time.

For the BFO-ANC system with the reported set of parameters value, the simulations show that the tracking capability is well enough to reach considerably acceptable results in noise cancellation performance. For the first input noise sample, the proposed ANC system optimises the adaptive filter weights with the initialised values. After that, the system uses the current weight values (trained based on the previous noise sample) as the starting point to adapt to the next noise sample. This gradual tracking capability leads to a reduction in the time needed for the ANC system to adapt to the next similar noise samples or more reduction of noise in the same time.

5 Conclusions

In this paper, a new evolutionary algorithm, known as BFO, was employed to optimise the adaptive controller of an ANC system, called BFO-ANC. Since linear active controllers do not usually perform well in non-linear situations, a non-linear control system was considered in this paper. Several computer simulations were developed in order to analyse the performance of the proposed BFO-ANC system. The experiments were performed in two major groups including a linear and a non-linear secondary path, along with a non-linear primary path. In each group, the effect of different parameters of the BFO algorithm was investigated on the performance and robustness of the proposed ANC system. We also compared the results obtained by the three ANC systems; the proposed BFO-ANC, the GA-based ANC and the filtered-X LMS-based ANC. The simulation results demonstrated the effectiveness of the proposed BFO method in noise cancellation performance under several situations.

6 References

1 Kuo, S.M., Morgan, D.R.: 'Active noise control systems-algorithms and DSP implementation' (Wiley, New York, 1996)

2 Elliott, S.J.: 'Signal processing for active control' (Academic, London, UK, 2000)

3 Elliott, S.J., Nelson, P.A.: 'Active noise control', *IEEE Signal Process. Mag.*, 1993, **4**, (10), pp. 12–35

4 Er, M.J., Li, Z., Cai, H., Chen, Q.: 'Adaptive noise cancellation using enhanced dynamic fuzzy neural networks', *IEEE Trans. Fuzzy Syst.*, 2005, **3**, (13), pp. 331–342

5 Vikram Kumar, P., Prabhu, K.M.M., Das, D.P.: 'Block filtered-s least mean square algorithm for active control of non-linear noise systems', *IET Signal Process.*, 2010, pp. 168–180

6 Zhou, D., DeBrunner, V.: 'Efficient adaptive nonlinear filters for nonlinear active noise control', *IEEE Trans. Circuits Syst. I*, 2007, **3**, (54), pp. 669–681

7 Das, D.P., Panda, G.: 'Active mitigation of nonlinear noise processes using a novel filtered-s LMS algorithm', *IEEE Trans. Speech Audio Process.*, 2004, **3**, (12), pp. 313–321

8 Gholami Boroujeny, Sh., Eshghi, M.: 'Design of an ANC system using PBS-LMS algorithm in the secondary path modeling filter'. Proc. 38th Int. Conf. on Noise Control Engineering INTER-NOISE 2009, Ottawa, August 2009

9 Sicuranza, G.L., Carini, A.: 'Adaptive recursive FLANN filters for nonlinear active noise control'. Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), Prague, May 2011, pp. 4312–4315

10 Russo, F., Sicuranza, G.L.: 'Accuracy and performance evaluation in the genetic optimization of nonlinear systems for active noise control', *IEEE Trans. Instrum. Meas.*, 2007, **4**, (56), pp. 853–857

11 Chang, Ch.Y., Chen, D.R.: 'Active noise cancellation without secondary path identification by using an adaptive genetic algorithm', *IEEE Trans. Instrum. Meas.*, 2010, **9**, (59), pp. 2315–2327

12 Chang, C.Y., Shyu, K.K.: 'Active noise cancellation with a fuzzy adaptive filtered-x algorithm', *IET Circuits Dev. Syst.*, 2003, **5**, (150), pp. 416–422

13 Chang, C.Y., Louh, F.B.: 'Enhancement of active noise control using neural based filtered-X algorithm', *J. Sound Vib.*, 2007, **1–2**, (305), pp. 348–356

14 Bouchard, M., Pailard, B., Dinh, C.T.L.: 'Improved training of neural networks for nonlinear active control of sound and vibration', *IEEE Trans. Neural Netw.*, 1999, **2**, (10), pp. 391–401

15 Matsuura, T., Hiei, T., Itoh, H., Torikoshi, K.: 'Active noise control by using prediction of time series data with a neural network'. Proc. IEEE SMCC Conf., 1995, (3), pp. 2070–2075

16 Sicuranza, G.L., Carini, A.: 'Filtered-X affine projection algorithm for multichannel active noise control using second-order Volterra filters', *IEEE Signal Process. Lett.*, 2004, **11**, (11), pp. 853–857

17 Strauch, P., Mulgrew, B.: 'Active control of nonlinear noise processes in a linear duct', *IEEE Trans. Signal Process.*, 1998, **9**, (46), pp. 2404–2412

18 Tan, L., Jiang, J.: 'Adaptive Volterra filters for active noise control of nonlinear processes', *IEEE Trans. Signal Process.*, 2001, **8**, (49), pp. 1667–1676

19 Tang, K.S., Man, K.F., Kwong, S., He, Q.: 'Genetic algorithms and their applications', *IEEE Signal Process. Mag.*, 1996, **6**, (13), pp. 22–37

20 Yim, K.H., Kim, J.B., Lee, T.P., Ahn, D.S.: 'Genetic adaptive IIR filtering algorithm for active noise control'. Proc. IEEE Int. Conf. Fuzzy Systems, August 1999, pp. 1723–1728

21 Gholami Boroujeny, Sh., Eshghi, M.: 'Efficient adaptive noise cancellation using genetic optimization'. Proc. 10th Int. Conf. on Signal Processing (ICSP), Beijing, 2010, pp. 2596–2599

22 Passino, K.M.: 'Biomimicry for optimization, control, and automation' (Springer, 2005)

23 Passino, K.M.: 'Biomimicry of bacterial foraging for distributed optimization and control', *IEEE Control Syst. Mag.*, 2002, **3**, (22), pp. 52–67

24 Mishra, S.: 'A hybrid least square-fuzzy bacterial foraging strategy for harmonic estimation', *IEEE Trans. Evol. Comput.*, 2005, **1**, (9), pp. 61–73

25 Tripathy, M., Mishra, S.: ‘Bacteria foraging-based to optimize both real power loss and voltage stability limit’, *IEEE Trans. Power Syst.*, 2007, **1**, (22), pp. 240–248

26 Hanmandlu, M., Verma, O.P., Kumar, N.K., Kulkami, M.: ‘A novel optimal fuzzy system for color image enhancement using bacterial foraging’, *IEEE Trans. Instrum. Meas.*, 2009, **8**, (58), pp. 2867–2879

27 Rajamani, P., Day, D., Chakravorti, S.: ‘Classification of dynamic insulation failures in transformer winding during impulse test using cross-wavelet transform aided foraging algorithm’, *IET Elect. Power Appl.*, 2010, **9**, (4), pp. 715–726

28 Gholami Boroujeny, Sh., Eshghi, M.: ‘Active noise control using bacterial foraging optimization algorithm’. Proc. 10th Int. Conf. on Signal Processing (ICSP), Beijing, 2010, pp. 2592–2595

7 Appendix: proposed algorithm for BFO-ANC

The proposed algorithm for BFO-ANC system has three main steps is given in Fig. 10.

Step 1–Initialisation:

1) S, is the number of bacteria to be used for searching the total region. This parameter shows the number of individuals in first bacteria population. In this paper, each bacterium shows a string of filter weights.

2) p, is the dimension of the search space or the number of parameters to be optimised.

3) N_s, is the swimming length that after each tumbling of bacteria will be undertaken in a chemotactic loop.

4) N_c, is the number of iterations to be undertaken in a chemotactic loop, ($N_c > N_s$).

5) N_{re}, is the maximum number of reproductions to be undertaken.

6) N_{ed} is the maximum number of elimination and dispersal events to be imposed over the bacteria.

7) P_{ed}, is the probability with which the elimination and dispersal will continue.

8) P, is the location of each bacterium in the first bacteria population.

9) $C(i)$, is the size of the step taken in the random direction specified by the tumble for each bacterium. In our case, this is assumed to be constant for all the bacteria.

Step 2–get the incoming noise samples: In this step the input noise samples to the ANC system is taken. For each noise sample the algorithm runs separately and the corresponding residual noise is obtained.

Step 3–Iterative Algorithm for Optimisation: This section models the bacterial population chemotaxis, reproduction, elimination and dispersal (initially, $j = k = l = 0$). For the algorithm updating θ^i automatically results in updating of P.

1) Elimination-dispersal loop: $l = l + 1$

2) Reproduction loop: $k = k + 1$

3) Chemotaxis loop: $j = j + 1$

   a) For $i = 1, 2, \ldots, S$, take a chemotactic step for bacterium i as follows

   b) Compute cost function, $J(i, j, k, l)$.

   c) Let $J_{last} = J(i, j, k, l)$ to save this value since we may find better value via a run.

   d) Tumble. Generate a random vector $\Delta(i) \in R^n$ with each element $\Delta_m(i), m = 1, 2, \ldots, p,$ a random number on $[-1, 1]$.

   e) Move. Let

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}. \qquad (9)$$

   This results in a step of size $C(i)$ in the direction of the tumble for i^{th} bacteria.

   f) Compute $J(i, j+1, k, l)$ with $\theta^i(j+1, k, l)$.

   g) Swimming

      i. Let $m = 0$ (counter for swim length).

      ii. While $m < N_S$ (if has not climbed down too long), the following hold

Fig. 10 *Proposed algorithm for BFO-ANC*

doi: 10.1049/iet-spr.2011.0092

- Let $m = m + 1$.
- If $J(i, j+1, k, l) < J_{last}$ then let $J_{last} = J(i, j+1, k, l)$, then another step of size $C(i)$ in this same direction will be taken as Eq. (9), and use the new generated.
- Use $\theta^i(j+1, k, l)$ to compute the new $J(i, j+1, k, l)$.
- Else let $m = N_S$. This is the end of the while statement.

h) Go to next bacterium, $(i+1)$. If $i \neq S$, go to (b) to process the next bacterium.

4) If $j < N_c$, go to Step 3. In this case, continue chemotaxis since the life of the bacteria is not over.

5) Reproduction

a) For the given k and l, and for each $i = 1, 2, \ldots, S$, let

$$J^i_{health} = \min[J(i, j, k, l)] \quad for\ j = 1, \ldots, N_C + 1. \tag{10}$$

This signal is the health of the bacterium i.

b) The $S_r = S/2$ bacteria with the highest J_{health} values die and the other S_r bacteria with the best values split and the copies that are made are placed at the same location as their parent.

6) If $k < N_{re}$, go to Step 2. In this case the number of specified reproduction steps is not reached and start the next generation in the chemotactic loop.

7) Elimination-dispersal: for $i = 1, 2, \ldots, S$, with probability p_{ed}, eliminate and disperse each bacterium, which results in keeping the number of bacteria in the population constant. To do this, if a bacterium is eliminated, simply disperse one to a random location on the optimisation domain. If $l < N_{ed}$, then go to Step 2; otherwise end.

Fig. 10 *Continued*