Adaptive filtering method for EMG signal using bounded range artificial bee colony algorithm

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Abstract

In this paper, an adaptive artefact canceller is designed using the bounded range artificial bee colony (BR-ABC) optimization technique. The results of proposed method are compared with recursive least square and other evolutionary algorithms. The performance of these algorithms is evaluated in terms of signal-to-noise ratio (SNR), mean square error (MSE), maximum error (ME) mean, standard deviation (SD) and correlation factor (r). The noise attenuation capability is tested on EMG signal contaminated with power line and ECG noise at different SNR levels. A comparative study of various techniques reveals that the performance of BR-ABC algorithm is better in noisy environment. Our simulation results show that the ANC filter using BR-ABC technique provides 15 dB improvement in output average SNR, 63 and 83% reduction in MSE and ME, respectively as compared to ANC filter based on PSO technique. Further, the ANC filter designed using BR-ABC technique enhances the correlation between output and pure EMG signal.

Keywords Ant colony optimization · Gradient methods · Design optimization · Mean square error methods · Adaptive estimation

1 Introduction

The electromyogram (EMG) represents a superposition of electrical activity from motor unit action potentials located subcutaneous to the detecting electrodes. EMG provides valuable information relating to peripheral and central motor function and has been widely adopted in the study of motor function and movement disorders including dystonia [1, 2]. The dystonia is a clinical syndrome characterised by twisting, abnormal posture, repetitive movements and pain resulting from sustained muscle contractions. Surface EMGs obtained from patients with dystonia are inherently non-stationary due to unstable and mixed symptoms which contain substantial levels of noise [2]. In addition to this, there are several other prominent artefactual sources which should also be taken into consideration. In the past, surface EMGs have been applied quantitatively to assess muscular activity in dystonia and to study its pathophysiological

features [2, 3]. In surface EMGs of dystonic patients, it is found that there is short bursting activity superimposed on sustained tonic activity [2–4]. Recently, novel measures suggest that the patients with a dominant bursting pattern of EMG activity have quicker and better improvement after pallidal deep brain stimulation (DBS), and an invasive stereotactic neurosurgical procedure [5]. It has been suggested that the dystonic activity may be due to over-synchronised pallidal oscillations in 3–20 Hz range [5, 6]. However, clear separation of the mechanisms responsible for bursting and sustained muscular activation remains elusive [3]. These findings were limited by the contamination of EMG recordings due to the electrocardiogram (ECG) artefacts which were especially pronounced from the shoulder and neck muscles of the patient with cervical dystonia. Therefore, the unwanted signals in EMG include power line interference and ECG coupling. The power line interference can be easily removed using suitable notch filters [7]. Whereas, separation of ECG from the surface EMG recordings is a difficult task due to their inherent overlap in frequency and temporal domains. Several studies have been reported for removal of ECG noise from the surface EMGs by applying high-pass filters, subtraction or

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gating operation methods [6]. Karan et al. [8] investigated the influence of adjusting the cut-off frequency of a high-pass filter and suggested that a cut-off frequency of approximately 30 Hz may be optimal for removing ECG contamination in EMG signal. A subtraction procedure as reported in [6–10] provides an alternate solution by detecting and aligning QRS complexes, averaging the aligned activity and subtracting the averaged artefacts from EMG via a least-square fit. The efficacy of this method relies on the accuracy of QRS complex detection and the degree of stationarity of EMG signal. On the other hand, the gating method provides a simplistic yet potentially effective procedure for removing ECG artefact [11–13]. However, this method suffers from losing the portions of the EMG signal which overlap with QRS complexes in amplitude [11]. Recently, more sophisticated signal processing algorithms including the application of nonlinear state-space projections [12], wavelet-threshold de-noising [3], independent components analysis (ICA) [1] and combinations of Neural-ICA have been used for artefact suppression in the surface EMGs. Later on, Weiner and Kalman filters [13] were used in designing of ANC filter based on the relative characteristics of ECG and EMG signals i.e. the frequency overlap, non-stationary, varied temporal shape and low signal-to-noise ratio (SNR) to achieve optimal de-noising performance.

The literature review explores that various types of algorithms or error estimation methods have been exploited in adaptive filters to adjust the weights of filter, and error estimation according to EMG signal and noise properties [4, 5]. Most efficient gradient based algorithms are least mean square (LMS), recursive least mean (RLS) and their different variants [14]. These techniques encounter some problems of convergence, analyzing the non-linear and non-stationary processes, and partial overlap of signal and noise band-widths. Recently, swarm intelligence based evolutionary techniques such as genetic algorithm (GA), particle swarm optimization (PSO) [15–17], quantum particle swarm optimization (QPSO) [18], cuckoo search (CS) [19], modify cuckoo search (MCS) have emerged as robust tools for solving linear and non-linear equations [20]. These techniques utilize the concept of random population generation which acts as possible solutions. It is reported that these algorithms have slower convergence rate with higher computation time. These drawbacks were overcome by other evolutionary algorithms known as artificial bee colony (ABC), and artificial bee colony modify rate (ABC-MR) employed for adaptive filter design [15]. The ABC-MR technique was used to optimise only the positive filter coefficients while neglecting the negative coefficients which lead to non-perfect reconstruction of original signal. In order to minimise the mean-square-error (MSE), the concept of “Bounded Range (BR)” may be adopted in

ABC technique [21]. In this method, the range of search space (solution set) is declared as “ $\pm R$ ” (R integer or float number) that covers the random number generation and updating coefficients during execution of the algorithm. Further, the range is modified as “ $R \pm C$ ” (C is also an integer or float value) in which “ C ” acts as the control or bound over “ R ” such that the behavioural analysis of BR-ABC is done with increasing colony size and Bees range. To the best of our knowledge, the ANC filter based on BR-ABC is not reported in literature. Therefore, the motivation of this work is to propose an ANC filter design based on BR-ABC algorithm for efficient recovery of EMG signal. It is demonstrated that the ANC filter based on BR-ABC algorithm exhibits better fidelity parameters as compared to the reported ANC filter designed with ABC, ABC-MR, CS, MCS, QPSO, PSO and RLS methods. The proposed ANC filter structure is an effective way of de-noising the EMG signal which improves SNR, mean-square-error (MSE), maximum-error (ME) and correlation factor significantly.

2 ANC filter design based on BR-ABC algorithms

Explaining research chronological including research design, the research procedure in the form of an adaptive filter works as a noise canceller due to its self-learning process in which filter coefficients are adjusted in iterations in order to minimize the error [21]. The ANC filter design was reported using gradient based techniques such as LMS, and RLS methods [14] which were employed to filter the power line and electrooculogram (EOG) noise from ECG signal. Recently, the evolutionary techniques such as QPSO, PSO, CS, MCS and ABC, ABC-MR were used to optimize the ANC filter coefficients for efficiently reconstruction of ECG signal [22]. However, these algorithms are not applied for designing of ANC filter for de-noising of EMG signal. Therefore, in this work, the design of ANC filter using QPSO, PSO, CS, MCS, ABC, ABC-MR and BR-ABC along with gradient based techniques is proposed.

The block diagram of ANC filter using BR-ABC is shown in Fig. 1. The noisy EMG signal ($d(n)$) contains the pure EMG signal ($s(n)$) and noise ($q(n)$). In case of EMG signal, $q(n)$ consists of high frequency components (power line noise) and low frequency components (ECG noise) which are additive and uncorrelated with $s(n)$. In this work, signal $d(n)$ is taken from MIT-BIH data base [23]. In Fig. 1, $q_1(n)$ and $q_2(n)$ are high and low frequency noise, respectively which are generated using Matlab. It may be noted that the $q_1(n)$ and $q_2(n)$ are correlated with $q(n)$ but uncorrelated with $s(n)$. The reference noise $q_1(n)$ and $q_2(n)$ are fed to ANC filter to produce output $y_1(n)$ and $y_2(n)$, respectively. The error signal ($e_1(n)$) is computed as the

Fig. 1 Block diagram of an ANC filter

difference of $d(n)$ and $y_1(n)$, which is fed back to the ANC filter in each iteration. The iteration process will continue till $e_1(n)$ or the high frequency noise is minimized in first stage. The output signal, $s(n) + q'(n)$ containing low frequency noise is given to the second stage of ANC filter where the error signal ($e_2(n)$) is computed as the difference of $s(n) + q'(n)$ and $y_2(n)$. The $e_2(n)$ is fed back to ANC filter in each iteration till $e_2(n)$ is minimized. The final output signal ($s'(n)$) is nearly equal to $s(n)$. The error function for $e_1(n)$ and $e_2(n)$ is represented by [23]:

$$\text{Error function} = \frac{1}{M} \sum_{i=1}^M e_{ij}^2(m) \quad (1)$$

where $e_{ij}(m)$ is j th error of i th sample for m th iteration and M is the total number of samples of applied input signal. A conventional adaptive filter optimization algorithm provides only one possible solution after every iteration [15–19]. To obtain a range of possible solution in each iteration, various algorithms are used to formulate the ANC problem as an optimization problem so that the probability of achieving the global optimum is increased [16, 17, 21].

The ABC algorithm may be effectively utilized in optimization of non-linear problems [18]. This algorithm is simple as well as flexible compared to other optimization techniques and provides a very good convergence rate. The position vector of ABC algorithm is initialized as $X_i = (X_{i,1}, X_{i,2}, \dots, X_{i,D})$, which represents the i th solution in population having ' D ' dimension. The initial random population is generated according to following equation [21]:

$$X_{ij} = X_{\min,j} + \text{rand}(0, 1) * (X_{\max,j} - X_{\min,j}) \quad (2)$$

where $i = 1, 2, \dots, S_N$, and $j = 1, 2, \dots, D$. The colony size is represented by S_N and parameters $X_{\min,j}$ and $X_{\max,j}$ are the minimum and maximum bounds having j dimension, respectively. In the next step, a new position for each employed bee in ABC algorithms is calculated as [21]:

$$V_{ij} = X_{ij} + (\text{rand} - 0.5) * (X_{ij} - X_{k,j}) \quad (3)$$

where $k = 1, 2, \dots, S_N$ is a randomly chosen index. Although, k is determined randomly but it is different from i and $(\text{rand} - 0.5)$. Finally, the fitness value for ' V ' is computed and the best one is selected by comparing the best fitness value between V_i and X_i . The probabilistic selection process is done by the onlooker bees in ABC algorithm to select position defined [21]:

$$P_i = \frac{\text{fit}_i}{\sum_{i=1}^{S_N} \text{fit}_i} \quad (4)$$

where fit_i is the fitness value of i th solution. Higher the fit_i , more is the probability that the i th food source is selected. P_i is the selection probability of i th food source by onlooker bee. After selecting food source X_i by the onlooker, a modification in X_i is performed by Eq. (2). At the last, the food sources which cannot be further enhanced within the predefined trials (limits) are supposed to be abandoned and the corresponding bees are declared as scout bees. Random food sources are assigned to scout bees. In this work, the ABC algorithm is employed to calculate the optimum weights of an ANC filter to minimize the mean square error (MSE). Figure 2 shows the flow chart of implementation of BR-ABC process. In a practical case, the complete input signal is not given to the ANC filter at one time i.e. the optimum weight vector changes in each iteration. In other words, a window or samples of the input signal are fetched in every iteration. In this method, the objective function (cost function) represents an estimate of MSE over the input samples used in that iteration. The fitness function to evaluate fitness of solution is formulated as:

$$\text{Fi} = \frac{1}{1 + J_i^{(n)}} \quad (5)$$

Fig. 2 Implementation of ANC filter using BR-ABC algorithm

Initialization of population in swarm intelligence techniques is done within the range $(\pm R)$. As per proposed modified range selection method, a constant “C” is taken as bound over range “R”. Finally, simulation is performed with increasing range of “R” which leads to range selected in the form of “ $R \pm C$ ”. In BR-ABC algorithm, the simulation is performed for varying range of bees (solution values) from 1 to 100 which has movement ± 2 for each noise level and the colony size is modified to $P_n = P_{n-1} + 2$ in each iteration. Initial value of colony size is taken as 2 which reaches 100 in last iteration. In this work, a new concept to define the range is proposed in which range variable “R” is controlled by a constant “C”. The difference between the conventional and the proposed approach is more clearly visualized from Fig. 3. It is observed that in case of the conventional approach, the search space is large when “R” is increased from $-R$ to $+R$ covering more space to generate new solutions. However, in this case, it is difficult to find optimum solution. On the other hand, in case of the proposed approach, the search space is constant as “ $R \pm C$ ” with new solution bounded with a constant “C” providing smaller search area which is good to find optimum solution.

The EMG data used in this work is taken from MIT data set [23]. This data was obtained from two healthy subjects and six patients diagnosed with primary cervical dystonia. For dystonic patients, the surface EMGs were recorded using disposable adhesive Ag/AgCl electrodes (H27P, Kendall-LTP, MA, USA) placed bilaterally over symptomatic trapezius and sternocleidomastoid muscles. A single channel lead-II ECG was simultaneously recorded as a reference signal for adaptive filtering. Signals were simultaneously recorded from bilateral trapezius muscles during rest and head-rotational movement. These signals were amplified using isolated CED 1902 amplifiers (1000×), filtered at 0–1000 Hz and digitised using CED 1401 mark-II at a sampling rate of 2500 Hz. ECG artefacts from the left trapezius muscle of healthy controls at rest were mixed with ECG free surface EMGs from right trapezius during head-rotation to generate contaminated EMG signals. This procedure allowed ECG contaminated EMG signals to be simulated with varying SNRs.

Fig. 3 **a** Conventional search space approach ($\pm R$) [23]. **b** Proposed controlled search space approach $R \pm C$

3 Results and analysis

The performance of ANC filter designed using different evolutionary algorithms such as QPSO, PSO, CS, MCS, ABC, ABC-MR and BR-ABC algorithms is evaluated on EMG signal corrupted with 10 dB noise [23]. The reference noise taken in this study is a random noise generated using Matlab with length of 1000. The fidelity parameters such as output signal-to-noise ratio (SNR), MSE, maximum error (ME) and correlation factor (r) are computed by varying input SNR. These fidelity parameters are calculated using following equations [15]:

At input, the SNR is calculated as:

$$\text{SNR (dB)} = 10 \log_{10} \frac{(EMG_{\text{pure}})^2}{(EMG_{\text{noisy}} - EMG_{\text{pure}})^2} \quad (6)$$

At output, the SNR is calculated as:

$$\text{SNR (dB)} = 10 \log_{10} \frac{(EMG_{\text{pure}})^2}{(EMG_{\text{filter}} - EMG_{\text{pure}})^2} \quad (7)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (EMG_{\text{noisy}} - EMG_{\text{pure}})^2 \quad (8)$$

$$\text{ME} = \text{abs}(EMG_{\text{filter}} - EMG_{\text{pure}})^2 \quad (9)$$

$$r = \frac{N \Sigma xy - \Sigma x \Sigma y}{\sqrt{N [\Sigma x^2 - (\Sigma x)^2]} \sqrt{N [\Sigma y^2 - (\Sigma y)^2]}} \quad (10)$$

where x and y are the pure and filtered output EMG signals, respectively. In response to the corrupted EMG signal, the amplitude of ANC filter output using RLS, PSO, MCS and BR-ABC techniques is shown in Fig. 4. The signal sources of Fig. 4a–c are MIT-BIH EMG database [19] and Matlab, respectively. Figure 4d–g show the reconstructed EMG

Fig. 4 Enhancement of EMG signal using proposed ANC filter based on different techniques: **a** noisy EMG signal, **b** reference noise at high frequency, **c** reference noise at low frequency, **d** output EMG signal

using RLS, **e** output EMG signal using PSO, **f** output EMG signal using MCS and **g** output EMG signal using BR-ABC technique

Table 1 Comparison of SNR performance of various techniques on EMG signals

Input SNR (dB)	Output SNR (dB)							
	RLS [14]	PSO [16]	QPSO	CS	MCS	ABC	ABC-MR	BR-ABC
− 5.0	3.78	3.87	2.56	1.98	2.34	2.12	3.48	4.88
0.5	23.45	40.67	32.21	36.64	39.56	38.41	40.31	41.32
3.0	34.65	44.86	38.02	45.11	47.34	46.22	49.32	51.45
6.0	35.65	47.87	40.54	52.01	53.34	53.14	54.64	55.54
10	38.87	58.23	47.65	61.21	68.23	64.43	71.42	73.43

Fig. 5 Comparison of output SNR performance of the ANC filter based on BR-ABC, MCS, PSO and RLS algorithms **Table 2** A comparison of MSE of EMG signal for various techniques on EMG signals

Input SNR (dB)	MSE ($\times 10^{-6}$)							
	RLS [14]	PSO [16]	QPSO	CS	MCS	ABC	ABC-MR	BR-ABC
− 5.0	11.23	9.23	10.21	9.89	9.50	10.40	5.40	4.40
0.5	10.00	8.41	9.40	8.65	7.82	9.22	6.30	4.30
3.0	9.60	8.56	9.51	8.40	6.41	7.21	4.31	3.31
6.0	8.43	7.60	8.61	6.23	5.53	6.33	3.23	1.23
10	4.90	4.20	4.32	3.21	2.50	3.46	1.56	0.56

signal using ANC filter based on RLS, PSO, MCS and BR-ABC, respectively. It is clearly seen that the ANC filter with BR-ABC algorithm provides higher amplitude of EMG signal. Therefore, BR-ABC technique allows more accurate detection of EMG signal information. The simulated output SNR with variation in the input SNR for different algorithms is listed in Table 1. A comparison of output SNR for different algorithms is also plotted in Fig. 5. It is observed that the output SNR performance of ANC filter with BR-ABC algorithm is better than that of the PSO, MCS and RLS algorithms. The average output average SNR of MCS and BR-ABC techniques is 9 and 15 dB higher than the conventional PSO technique. The variation of MSE as a function of input SNR is given in Table 2 which is plotted in Fig. 6 for ANC filter using different techniques. As seen, the MSE performance of BR-ABC algorithm is much better than other techniques. A reduction in average MSE of 16 and 63% with MCS and BR-ABC algorithms, respectively, can be obtained when

compared with the PSO technique. The variation of ME with input SNR is given in Table 3. Figure 7 shows the plot of ME of output EMG signal for different levels of input SNR. The ANC filter with BR-ABC algorithm achieves significant reduction in ME as compared to the PSO and MCS algorithms at higher value of input SNR. The average ME of filtered EMG signal with MCS and BR-ABC techniques is found to be 20 and 83%, respectively lower than that with PSO algorithm. Figure 8 shows the coherence between pure EMG and reconstructed EMG signals using ANC filter with BR-ABC and MCS techniques. As seen, the BR-ABC algorithm exhibits higher coherence factor as compared to the MCS technique.

For the analysis of adaptation time, the square error of adaptive filters is analyzed with mean and standard deviation. Table 4 lists the mean and standard deviation (SD) of different algorithms along with computational time. The ABC-BR based adaptive noise canceller is having lowest mean, SD and computational complexity.

Fig. 6 Variation of MSE with input SNR for the ANC filter based on RLS, PSO, MCS and BR-ABC algorithms

Table 3 A comparison of ME of EMG signal for various techniques

Input SNR (dB)	ME ($\times 10^{-5}$)							
	RLS [14]	PSO [21]	QPSO	CS	MCS	ABC	ABC-MR	BR-ABC
5.0	62.62	42.12	52.12	49.01	45.18	48.33	15.13	11.3
0.5	48.44	28.5	38.51	45.23	42.23	43.72	13.52	9.72
3.0	42.42	23.4	33.42	36.10	26.23	36.32	16.44	6.35
6.0	38.90	15.6	25.61	31.10	26.33	53.32	9.46	5.42
10	28.21	9.42	15.42	24.60	20.44	23.31	8.45	3.94

Fig. 7 ME as a function of input SNR for the ANC filter based on BR-ABC, MCS, PSO and RLS algorithms

Fig. 8 Comparison of coherence performance of the ANC filter based on MCS and BR-ABC algorithms

Table 4 Mean, standard deviation and simulation time of adaptive noise canceller

Parameter	RLS [14]	PSO [16]	QPSO	CS	MCS	ABC	ABC-MR	ABC-BR
Mean	1.8056	1.635	1.865	1.531	1.421	1.261	1.0609	1.0201
SD	28.998	19.231	22.761	1.843	1.786	1.341	1.7407	1.421
Simulation time (s)	0.278	0.126	0.651	0.0831	0.0821	0.0665	0.0487	0.0186

4 Conclusion

The ANC filter design using BR-ABC optimization method has been presented for de-noising of EMG signal. A performance comparison of ANC filter designed with different techniques has been carried out. The improvement in SNR, MSE, ME, and correlation factor illustrates the superiority of proposed ANC filter with BR-ABC when compared with other algorithms. This work demonstrates that significant improvement in all fidelity parameters on EMG signal can be obtained with ANC filter based on BR-ABC algorithm. Therefore, the proposed technique is very attractive approach for de-noising of EMG signal.

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Compliance with ethical standards

Conflict of interest None.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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