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ORIGINAL ARTICLE

# Extraction of Cole parameters from the electrical bioimpedance spectrum using stochastic optimization algorithms

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**Abstract** Fitting the measured bioimpedance spectroscopy (BIS) data to the Cole model and then extracting the Cole parameters is a common practice in BIS applications. The extracted Cole parameters then can be analysed as descriptors of tissue electrical properties. To have a better evaluation of physiological or pathological properties of biological tissue, accurate extraction of Cole parameters is of great importance. This paper proposes an improved Cole parameter extraction based on bacterial foraging optimization (BFO) algorithm. We employed simulated datasets to test the performance of the BFO fitting method regarding parameter extraction accuracy and noise sensitivity, and we compared the results with those of a least squares (LS) fitting method. The BFO method showed better robustness to the noise and higher accuracy in terms of extracted parameters. In addition, we applied our method to experimental data where bioimpedance measurements were obtained from forearm in three different positions of the arm. The goal of the experiment was to explore how robust Cole parameters are in classifying position of the arm for different people, and measured at different times. The extracted Cole parameters obtained by LS and BFO methods were applied to different classifiers. Two other evolutionary algorithms, GA and PSO were also used for comparison purpose. We showed that when the classifiers are fed with the extracted feature sets by BFO fitting method, higher accuracy is obtained both when applying on training data and test data.

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**Keywords** Bioimpedance spectroscopy (BIS) · Cole model · Bacterial foraging optimization (BFO) · Feature extraction · Classification

## 1 Introduction

Bioimpedance spectroscopy (BIS) is a technique for biological tissue monitoring that has been widely used in many applications because it is safe, non-invasive, has fast response and low cost [14, 22, 23, 33]. For instance, it has been successfully used in characterization of body tissues for early disease diagnosis [31], determination of body water content [13, 18, 32], and muscle and cardiovascular activity [17]. In most of the applications, the measured bioimpedance spectrum needs to be computationally processed to extract useful information contained in it. In spite of extensive range of methods introduced by researchers, using the Cole model to fit the measured BIS data and then extracting the Cole parameters is widely accepted way to explain the biological tissue properties or to do a classification task based on the extracted parameters, and has been successfully applied in many researches [2, 6, 7, 11, 19, 20, 29]. The choice of an appropriate numerical fitting method that is less effected by the noise caused by the data acquisition process, can result in more accurate extracting the information from the measured data and finally a better explanation of the biological tissue properties [19, 20, 29].

Deterministic gradient methods such as least squares (LS) fitting methods are usually used for Cole model fitting of the BIS data. Although they are computationally efficient, their fitting performance is not robust to the noise and outliers. In most BIS applications the accuracy of parameter estimation is more important than the execution time [10, 29]. These gradient methods have high dependency to

the initial values and in case of noisy data, their premature convergence or convergence to local minima results in producing parameter sets that deteriorate the classification [29, 34].

Most of the methods used in the literatures are based on the LS fitting methods whereas the techniques based on stochastic optimization methods such as GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) have been only used in a few BIS applications [15, 29]. Researchers in [15] applied both genetic and least squares algorithms to fit a Cole model to the data measured from the prostatic tissues. Based on their reports, both the algorithms fit the measured data well with the least square algorithm having a better average fitting performance. In [29] both LS and PSO algorithms have been applied to a bovine tissue classification problem while the signal-to-noise ratio (SNR) of the experimental data was changed by adding white Gaussian noise to the experimental data points. They showed that when the extracted parameters obtained by LS and PSO fitting methods fed to the classifier, the PSO method demonstrates a better classification rate and a higher noise tolerance than the LS method. However, the drawback of PSO is that the method does not have enough accuracy in the regulation of its speed and the direction of the particles. As a result, the swarm may prematurely converge and be trapped in local area, thereby the algorithm can not work out the global optimization problems [3, 9].

A new algorithm from the family of evolutionary computation which is based on foraging behavior of bacteria, known as bacterial foraging optimization (BFO) algorithm, has been recently proposed [27, 28]. The BFO algorithm is based on the foraging behavior of bacteria where bacteria search for nutrients in order to maximize the energy obtained per unit time. Owing to its robust performance and simple structure, this algorithm has drawn the attention of many researchers from diverse fields of knowledge [1, 12, 16, 21, 24]. It has already been applied to many real world problems and its effectiveness over many variants of genetic algorithm (GA) and particle swarm optimization (PSO) has been proved [8, 21, 30].

In this paper, we propose an improved Cole fitting method based on bacterial foraging optimization (BFO) algorithm. We apply BFO as a stochastic optimization algorithm for fitting BIS data to the Cole model. Computer simulations are carried out to investigate the performance of the BFO based Cole fitting by considering the accuracy in extracted Cole parameters and the robustness of the fitting performance to the noise. Then, the results are compared with those based on the LS-based curve fitting method, on simulated datasets. In addition, a classification task for determining the position of the arm is investigated on the experimental data where bioimpedance measurements were obtained from forearm in three different positions. The extracted Cole parameters obtained by LS and BFO methods were fed to different classifiers to test the classification accuracy by applying different classifiers on the training and test data. The goal of the classification is to investigate how robust the extracted Cole parameters are in classifying the position of the arm for different people while the measurements are obtained over different experiment sessions.

The rest of paper is organized as follows. In Sect. 2, the Cole parameters extraction from the bioimpedance measured spectra is first discussed and then we introduce the BFO algorithm and explain how to apply this algorithm to the problem of the fitting the bioimpedance spectra to the Cole model. In Sect. 3, the fitting performance of LS and BFO methods by applying on the simulated datasets is investigated. In Sect. 4 the classification results based on the experimental dataset are presented. Two other evolutionary algorithms, GA and PSO are also used for comparison purpose and their classification results are also given in this section. The last section of the paper includes the discussions, concluding remarks and suggestions for future work.

## 2 Methods

### 2.1 Spectral parameter estimation

The bioimpedance spectrum is obtained by passing a low-level alternative current between electrodes through a biological structure, over a limited frequency range. The tissue then behaves like RC series and parallel circuit and the voltage drop between electrodes provides a measure of impedance. The BIS is usually obtained by measuring the real and imaginary parts of the impedance components or the modulus and phase angle. The Cole model [7] is a semi-circle in the complex plane of resistive part (on the horizontal axis) against the conjugate part of the reactance (on the vertical axis). This model, that is an empirically derived equation usually used to evaluate the BIS data, is given by:

$$Z(f) = R_\infty + \frac{R_0 - R_\infty}{1 + \left(j\frac{f}{f_c}\right)^\alpha}, \tag{1}$$

where $Z(f)$ denotes the complex impedance that is a function of frequency $f$. $R_0$ is the resistance at zero frequency, $R_\infty$ is the resistance at infinite frequency, $f_c$ is the characteristic frequency of the tissue and the value of power, $\alpha$, is a measure of the position of the center of the semi-circle below the horizontal axis.

Two different algorithms, LS and BFO were formulated to estimate four Cole parameters $[R_0, R_\infty, f_c, \alpha]$. The LS method used in this paper is the iterative LS algorithm

proposed in [19]. The BFO algorithm is explained in the following section.

### 2.2 The BFO algorithm

BFO is based on natural selection and its tendency to eliminate animals with poor foraging strategies and to favour those having successful strategies. The key idea of the algorithm is to simulate the swarm foraging of *Escherichia coli* (*E. coli*) bacteria and how they work together cooperatively. Bacteria search for nutrients in a way to maximize energy obtained per time and to avoid threats at the same time. Briefly, the BFO algorithm can be separated in the following steps:

1. Initialization of the primary positions of the population of the bacteria and other parameters of the algorithm.
2. Evaluation of the position of the bacteria in the population, based on a defined fitness or cost function. In this paper the position of each bacterium is defined based on the Cole model parameters.
3. Chemotaxis; this process simulates the movement of bacteria through swimming and tumbling. Each bacterium can move in two different ways. It can swim for a period of time in the same direction or it can tumble, and interchanges between these two modes for its entire lifetime.
4. Swarming; an interesting group behavior is that the bacterium that has found the optimum path of food try to attract other bacteria so that they reach the desired place more rapidly. This helps the bacteria to congregate into groups and thus move as concentric patterns of groups with high bacterial density. As a result, the speed of convergence will be increased.
5. Reproduction; this process shows the selection and reproduction of the best bacteria based on their health. The health here is obtained by the sum of the accumulated costs or fitnesses of a bacterium during the bacterium's life span. For example, in a minimization problem where the goal is to minimize the cost function, bacteria are sorted based on ascending cost. The higher cost here means lower health. Half of the bacteria that are less healthy die while each of the healthier bacteria with better fitness value splits into two bacteria, at their own location. This makes the population of bacteria constant. In this paper, the number of reproduction steps is considered to be equal to 4 [27].
6. Elimination and Dispersal; gradual or sudden changes in the local environment that affect the lives of a population of bacteria. 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. This has the effect of possibly destroying the chemotactic progress, but it also has the effect of assisting in chemotaxis, since dispersal may place bacteria at better locations. This process prevents bacteria from being trapped in local optima. To simulate this in the algorithm, some of the bacteria are randomly reinitialized over the search space. In this paper, the number of elimination and dispersal events is chosen to be equal to 2, and for each elimination-dispersal event the probability that each bacterium in the population is subjected to elimination-dispersal is considered to be 0.25 [27].
7. Updating the position of bacteria based on the fitness function by repeating the iterative optimization algorithm (steps from 2 to 6) until a stopping condition is satisfied or simply by specifying a maximum number of iterations.

Our optimization problem here is to fit a measured bioimpedance spectrum to the Cole model. For this purpose, we define each bacteria in the optimization domain by a string of four parameters $[R_0, R_\infty, f_c, \alpha]$ of the Cole function, and so the dimension of the search space here is 4 as each of the parameters can be represented as one dimension in the search space.

In computational chemotaxis the movement update rule for the $i$th bacterium can be represented by:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}, \tag{2}$$

where $\theta^i(j,k,l)$ represents $i$th bacterium at $j$th chemotactic, $k$th reproduction and $l$th elimination-dispersal step. The maximum numbers of chemotactic, reproduction and elimination-dispersal steps are also shown with $N_c, N_{re}$ and $N_{ed}$, respectively. $C(i)$ is the run length unit that is the size of the step taken in the random direction specified by the tumble and $\Delta$ indicates a vector in the random direction whose elements lie in $[-1, 1]$, which represents a tumble.

BFO evaluates and updates the position of bacteria based on a fitness function defined as:

$$\text{fitness}(J) = \sum_{i=1}^{N} \text{abs}(Z_i - F_i), \tag{3}$$

where $Z_i$ shows the measured complex experimental BIS spectrum data points, $F_i$ shows the fitted spectrum data points and $N$ denotes the number of frequencies employed. The fitness value of $i$th bacterium at location $\theta^i(j,k,l)$ is now represented by:

$$J(i,j,k,l) = J(i,j,k,l) + J_{cc}\Big(\theta^i(j,k,l), P(j,k,l)\Big), \tag{4}$$

in which $P(j,k,l) = \{\theta^i(j,k,l); i = 1,2,...,S\}$ represents the position of the bacteria in the population where $S$ is the

number of bacteria to search the optimization space and $J_{cc}$ is the added fitness value by taking into account the swarming effect that denotes the combined cell-to-cell attraction and repelling effects, and defined by:

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{S}\left(\theta, \theta^i(j,k,l)\right) = \sum_{i=1}^{S}\left[-d_{\text{attract}} \times \exp\left(-w_{\text{attract}} \sum_{m=1}^{p}\left(\theta_m - \theta_m^i\right)^2\right)\right] + \sum_{i=1}^{S}\left[-h_{\text{repellant}} \times exp\left(-w_{\text{repellant}} \sum_{i=1}^{p}\left(\theta_m - \theta_m^i\right)^2\right)\right], \tag{5}$$

in which $d_{\text{attract}}$ is the depth of the attractant released by the cell, $w_{\text{attract}}$ is a measure of the width of the attractant signal, $h_{\text{repellant}}$ is the height of the repellant effect and $w_{\text{repellant}}$ is a measure of the width of the repellant and are chosen as 0.1, 0.2, 0.1 and 10, respectively [27, 28]. The number of bacteria $S$, the number of chemotactic steps and the size of run length unit $C(i)$ are their values are chosen as 100, 150 and 0.03, respectively. The algorithm is run for different values of the number of bacteria and the chemotactic steps. We chose these parameter values such that to have a satisfactory compromise between the accuracy in fitting and the execution time. Clearly, the larger number of these values increases the search ability of the algorithm, but also causes increase in the execution time. The block diagram of the BFO algorithm is shown in Fig. 1.

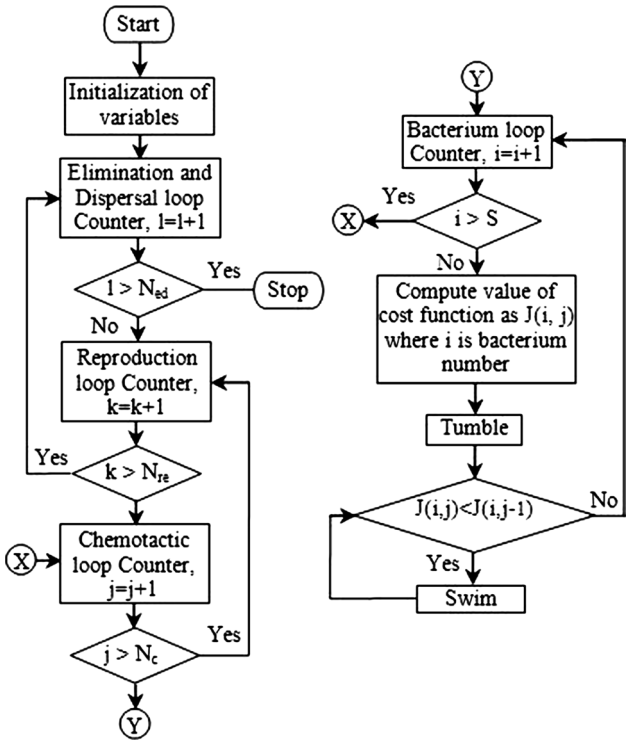


**Fig. 1** Block diagram of BFO algorithm

## 3 Spectral fitting results for simulated data

### 3.1 Simulated datasets

In this section, computer generated data is used to evaluate the performance of the algorithm in estimating the Cole parameters. The simulated data are generated from a Cole model with defined parameter values as the reference data, to which, two different levels of random noises, 0 to ± 10 % and 0 to ± 30 %, are added to produce two simulated datasets D1 and D2.

As the reference data, the 32 logarithmically distributed frequency points $(f_1, f_2, \ldots, f_{32})$ ranging from 1 kHz to 1 MHz of BIS data are generated using Eq. 1 based on a set of typical characteristic parameters of muscle impedance with parameters $R_0 = 150, R_\infty = 50\ \Omega, \alpha = 0.8$ and $f_c = 53.0516$ kHz [31]. All these data are exactly located on the Cole plot with circle center $(x_0, y_0) = (100, -16.2460)$ and radius $r_0 = 52.5731$.

Assuming $(x_{r_i}, y_{r_i})$ is the reference BIS data generated from the Cole equation, the data with added random noise is modelled according to the following Eq. [34],

$$\begin{cases} x_i = x_{r_i} + \beta \times \text{rand} \times r_0 \times \cos(\theta_i) \\ y_i = y_{r_i} + \beta \times \text{rand} \times r_0 \times \sin(\theta_i) \end{cases} \quad (i = 2, 4, ..., 32), \tag{6}$$

where $\theta_i$ denotes the angle between the horizontal axis and the radial direction at angular frequency $\omega_i$, and is calculated by the following equation:

$$\theta_i = \arccos\left(\frac{x_{r_i} - x_0}{r_0}\right), \tag{7}$$

rand represents random decimals with continuous uniform distributions on the interval $[-1, 1]$ and the coefficient $\beta$ is chosen to be 0.1 and 0.3 for datasets of D1 and D2, respectively. As a result, Dataset D1 is made of adding 0 to ± 10 % of radial random noises to the 16 even frequency points on the basis of the reference data [31]. For dataset D2, 0 to ± 30 % of radial random noises are added to the 16 even frequency points on the basis of the reference data.

### 3.2 Spectral fitting results

In this section, the curve fitting performance of BFO is compared with LS-based fitting for the simulated data. The

**Table 1** Fitting results of LS and BFO fitting methods for dataset D1 (mean value ± standard deviation)

| | Simulated data | | Fitting method | | | |
|---|---|---|---|---|---|---|
| | | | LS fitting | | BFO fitting | |
| $R_0$ | 150.0000 | $e_{R_0}(\%)$ | $150.14 \pm 0.82$ | $0.46 \pm 0.31$ | $150.00 \pm 0.13$ | $0.06 \pm 0.05$ |
| $R_\infty$ | 50.0000 | $e_{R_\infty}(\%)$ | $50.01 \pm 1.14$ | $1.81 \pm 1.36$ | $50.02 \pm 0.27$ | $0.41 \pm 0.35$ |
| $\alpha$ | 0.8000 | $e_\alpha(\%)$ | $0.79 \pm 0.02$ | $2.03 \pm 1.36$ | $0.80 \pm 0.00$ | $0.29 \pm 0.22$ |
| $f_c$ | 53.0516 | $e_{f_c}(\%)$ | $53.09 \pm 0.74$ | $1.15 \pm 0.78$ | $53.19 \pm 0.21$ | $0.39 \pm 0.27$ |

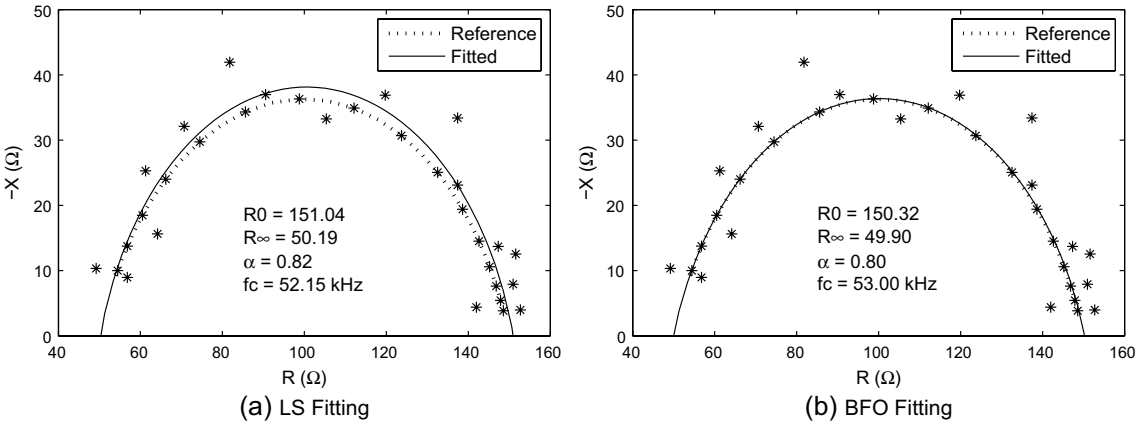


**Fig. 2** Fitted Cole plot based on LS and BFO methods for dataset D1 (0 to ± 10 % added random noises), dataset D1 (asterisk), Reference (harizontal dots), fitted (lines)

fitting performance is evaluated based on four target Cole parameters, $[R_0, R_\infty, \alpha, f_c]$.

The results of the 50 runs of the experiment for estimated Cole model parameters $[R_0, R_\infty, \alpha, f_c]$ and their related errors $[e_{R_0}(\%), e_{R_\infty}(\%), e_\alpha(\%), e_{f_c}(\%)]$ for dataset D1 are listed in Table 1. Since the random noises are generated differently at each time, data points distribution will be different in each run and so the fitting performance. To have a better evaluation of the fitting performance of applied fitting algorithms, the experiment is repeated 50 times. The data are shown as mean value ± standard deviation. The fitted Cole plots based on LS and BFO methods in one time run are shown in Fig. 2a, b. The results show that as the fitting performance of the LS method deteriorates by adding random noise to the original data points, the BFO method shows a better robustness to the noise in its fitting performance. The mean values of the percentage of the fitting error for four extracted Cole parameters $[R_0, R_\infty, \alpha, f_c]$ are obtained as $[0.46, 1.81, 2.03, 1.15\,\%]$ for LS method while those for BFO method are obtained to be $[0.06, 0.41, 0.29, 0.39\,\%]$.

The results of 50 runs of implementations of BFO and LS-based fitting for estimated Cole model parameters $[R_0, R_\infty, \alpha, f_c]$ for dataset D2 are listed in Table 2 (mean value ± standard deviation). Also the fitting results based on LS and BFO methods in one time run are shown in Fig. 3a, b. The results for dataset D2 show that while the LS method shows a considerable difference in the fitting performance with respect to the fitting performance for dataset D1, the fitting results for BFO are very close to the results for dataset D1. While the fitting errors for four extracted Cole parameters $[R_0, R_\infty, \alpha, f_c]$ are obtained as $[1.38, 4.35, 5.75, 2.76\,\%]$ for LS method, for BFO method the error results are obtained to be $[0.08, 0.32, 0.29, 0.62\,\%]$.

## 4 Classification results for experimental data

### 4.1 Experimental dataset

A set of forearm BIS measurements was performed using a *Solartron 1255 Frequency Response Analyser* and *1294 Impedance Interface*, with tetra-polar system [25]. Four *Ambu Blue Sensor T* electrodes were used which were single-use Ag/AgCL ECG electrodes. Current electrodes were placed in the middle between the wrist and the elbow and voltage electrodes were placed 1.5 inch distant from respective current electrodes. The data were collected from four subjects (30–35 years old, 2 female) in three different experiment sessions, and their forearm bioimpedance was measured in three different arm positions: horizontal (Hz), vertical pointing downward (VD) and vertical pointing upward (VU). Each specific measurement was repeated twice. The study procedures were approved by the

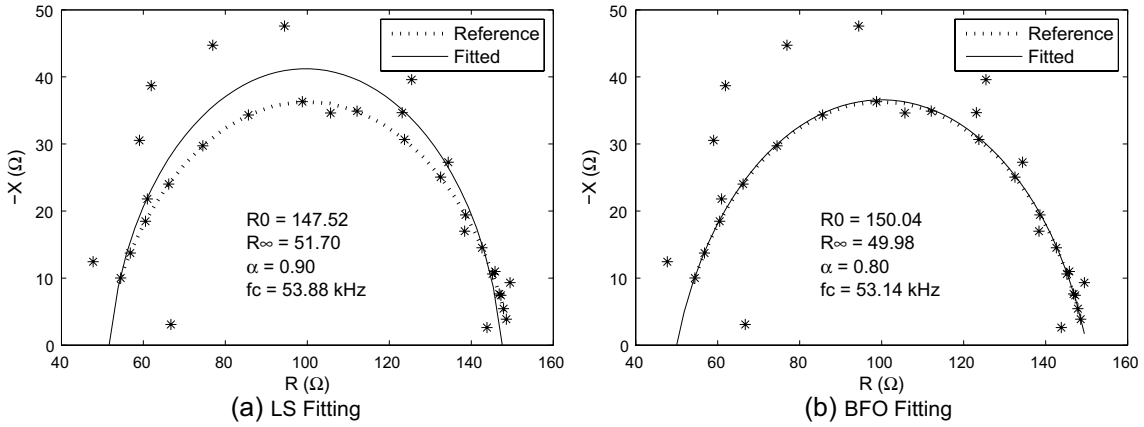


**Fig. 3** Fitted Cole plot based on LS and BFO methods for dataset D2 (0 to ± 30 % added random noises), dataset D2 (asterisk), Reference (harizontal dots), fitted (lines)

**Table 2** Fitting results of LS and BFO fitting methods for dataset D2 (mean value ± standard deviation)

| | Simulated data | | Fitting method | | | |
|---|---|---|---|---|---|---|
| | | | LS fitting | | BFO fitting | |
| $R_0$ | 150.0000 | $e_{R_0}(\%)$ | 150.14 ± 2.49 | 1.38 ± 0.91 | 149.99 ± 0.16 | 0.08 ± 0.07 |
| $R_\infty$ | 50.0000 | $e_{R_\infty}(\%)$ | 49.61 ± 2.83 | 4.35 ± 3.64 | 50.00 ± 0.22 | 0.32 ± 0.30 |
| $\alpha$ | 0.8000 | $e_\alpha(\%)$ | 0.79 ± 0.06 | 5.75 ± 4.82 | 0.80 ± 0.00 | 0.29 ± 0.26 |
| $f_c$ | 53.0516 | $e_{f_c}(\%)$ | 53.32 ± 1.87 | 2.76 ± 2.22 | 53.13 ± 0.38 | 0.62 ± 0.37 |

Research Ethics Board at the University of Ottawa, Ottawa, Ontario, Canada. Written informed consent was obtained from all participants in accordance with the Declaration of Helsinki prior to participation. All assessments were performed in a controlled laboratory environment.

A total of 72 (4 subjects × 3 positions × 3 sessions × 2 trials) impedance spectra were collected in this way at room temperature. The measured bioimpedance spectrum points contained 40 modulus and phase values at frequencies in the range from 5 up to 200 kHz with 5 kHz steps. A set of 12 pairs of reactance and resistance points corresponding to the lowest frequencies with negative reactance parts (from 5 to 60 kHz) was processed with BFO and LS-based fitting methods to fit the BIS data to the Cole plot and extract the model parameters.

### 4.2 Classification results

In this section the efficacy of BFO method in achieving a classification task on the forearm data is investigated. The goal of classification here is to investigate the effect of changing position on electrical properties variations of the forearm and to classify the BIS measured data based on the position in three different groups, Hz, VD and VU. However, it is worth mentioning that changes in arm's position will cause changes in other factors such as changes in geometry and blood perfusion. For example in [26], the volume of the blood within the arm segment is calculated by measuring the arm's resistance in different positions where the effect of the volumetric shift of blood is considered as a variable parallel electrical resistance. No classification was involved in study [26].

Both LS and BFO were used to fit the measured data for the different arm positions (Fig. 4). Four Cole parameters $[R_0, R_\infty, \alpha, f_c]$ were extracted after fitting the data to the Cole plot using BFO and LS methods. The mean of the results of the extracted spectral parameters for different forearm positions using BFO and LS fitting methods are listed in Table 3. The data in parenthesis corresponds to 95 % confidence intervals.

To evaluate and compare the robustness of the extracted Cole parameters by BFO and LS-based fitting methods in classifying the position of the arm, a classification task was implemented. We also applied GA and PSO algorithms for the Cole parameter extraction and arm position classification, to have a comparison with other evolutionary algorithms. For PSO and GA algorithms, we applied the same parameter settings as given in [29] and [15]. The extracted features by LS, BFO, GA and PSO methods were used as the input to different classifiers such as Linear and Quadratic discriminant analysis, decision tree and k-nearest neighbours (kNN) algorithms. Table 4 lists the percentage of classification results where each forearm position (Hz, VD and VU) is considered as a group in classification task.

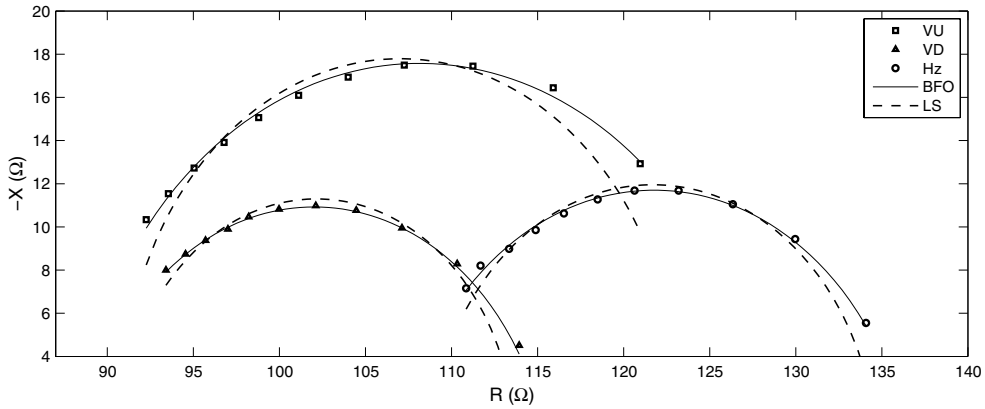


**Fig. 4** Example of fitted spectra of different arm positions (*vertical up*, *vertical down* and *horizontal*) by LS and BFO methods. *Markers* denote measured values. *Lines* denote fitted spectra

**Table 3** Mean spectral BIS parameters for different forearm positions

| Parameters | Hz | VU | VD |
|---|---|---|---|
| *LS* | | | |
| $R_0$ (Ω) | 102.55 (96.08–109.01) | 106.30 (99.83–112.77) | 105.02 (98.04–112.00) |
| $R_\infty$ (Ω) | 81.34 (79.42–85.26) | 84.07 (79.92–88.23) | 85.52 (81.08–89.95) |
| $\alpha$ | 0.72 (0.69–0.75) | 0.73 (0.69–0.78) | 0.69 (0.64–0.74) |
| $f_c$ (kHz) | 25.63 (24.28–26.99) | 25.22 (24.04–26.40) | 25.06 (23.89–26.22) |
| *BFO* | | | |
| $R_0$ (Ω) | 102.55 (96.14–108.97) | 106.40 (99.85–112.95) | 104.72 (97.87–111.56) |
| $R_\infty$ (Ω) | 81.46 (77.53–85.39) | 84.03 (79.87–88.20) | 85.76 (81.28–90.26) |
| $\alpha$ | 0.72 (0.69–0.77) | 0.74 (0.71–0.78) | 0.71 (0.66–0.76) |
| $f_c$ (kHz) | 25.47 (24.11–26.82) | 25.16 (24.02–26.30) | 25.07 (23.99–26.15) |

*Hz* horizontal, *VU* vertical upward, *VD* vertical downward. Means are shown for four Cole parameters extracted by LS and BFO fitting methods. Data in parenthesis show 95 % confidence intervals

**Table 4** Summary of arm position classification results on extracted Cole parameters by LS, BFO, GA and PSO methods (in percentage)

| Methods | Linear | | Quadratic | | Decision tree | | kNN | |
|---|---|---|---|---|---|---|---|---|
| | Resubsit. | Cross val. | Resubsit. | Cross val. | Resubsit. | Cross val. | Resubsit. | Cross val. |
| LS | 44.4 | 34.7 | 48.6 | 19.4 | 79.2 | 30.5 | 77.8 | 75.0 |
| BFO | $46.0 \pm 3.8$ | $37.1 \pm 3.5$ | $52.0 \pm 3.3$ | $28.8 \pm 3.5$ | $79.4 \pm 2.3$ | $39.0 \pm 4.0$ | $84.1 \pm 2.3$ | $82.2 \pm 2.5$ |
| GA | $42.0 \pm 4.1$ | $32.0 \pm 3.1$ | $46.0 \pm 3.9$ | $22.0 \pm 3.6$ | $78.1 \pm 2.5$ | $35.0 \pm 4.3$ | $75.4 \pm 3.1$ | $73.2 \pm 2.6$ |
| PSO | $46.5 \pm 3.4$ | $37.3 \pm 3.2$ | $50.0 \pm 3.6$ | $27.6 \pm 3.2$ | $79.1 \pm 2.1$ | $36.0 \pm 3.2$ | $78.6 \pm 2.7$ | $75.5 \pm 2.9$ |

Four different classifiers (linear discriminant analysis, quadratic discriminant analysis, decision tree and *k*-nearest neighbors) are applied on training data (resubsitution) and test data (by one-leave-out cross validation). Results for BFO, GA and PSO methods are shown as mean value ± standard deviation

Because of the randomness involved in BFO, GA and PSO search process, the results for these algorithms are obtained by averaging on classification results of 50 sets of extracted features and are presented as mean value ± standard deviation. We first applied each classifier on training data to compute the classification accuracy of each method by resubstitution. This provides us with the information about the fraction of the training data which is misclassified. Resubstitution fits a single classifier to the data, and applies this classifier in turn to each data observation. Since no test data is involved, resubstitution typically underestimates classifier error. In the next step we use cross validation in one-leave-out form to evaluate the methods in classifying by different classifiers when the test data is involved [5].

This validation method removes each data observation (here one Cole spectrum) in turn, constructs the classifier, and then computes whether the classifier correctly classifies the deleted spectrum.

As the results show, for almost all different types of classifiers the classification accuracy based on BFO method is higher than that based on LS method. In classifying the test data the best classification accuracy is obtained by using the KNN classifier. The number of neighbours equal to 2 ($k = 2$) gives us the best accuracy for both LS and BFO methods that is obtained by trial and error for different choices of the number of neighbours. The accuracy of classification method when applies on training data is always higher than that when tested with new observation data. However, by increasing the number of measurements to the dataset, the difference between classification on training data and prediction of test data by cross validation method will be reduced. From the results, in all the cases the difference between classification results on training data and test data for BFO is less than that for LS method. This is a promising result because it shows that the classifier based on BFO extracted dataset has less dependency on the training data and does not need a large number of measurements to train the classifier. Moreover, it shows that the extracted feature sets based on BFO have a higher potential to predict the class the new observation belongs.

## 5 Discussion

Fitting the measured bioimpedance spectroscopy (BIS) data to the Cole model is a very common practice for analysis of biological tissue through Cole parameters. The extracted Cole parameters can be used to describe the tissue electrical characteristics from tissue impedance spectra. To have a better description of tissue properties it is beneficial to extract the parameters of the best-fitted Cole model to the measured spectrum. This is not an easy task because the measured data points are always contaminated with noise, for example the noise from the measurement devices and electronic system such as the effects of parasitic capacitances, or the error caused during the acquisition process [4]. As a result, the data points never lie exactly on a circular curve. Moreover, the Cole model is a complex nonlinear function of frequency, thus the curve fitting and parameter extraction are inherently nonlinear problems.

To overcome these problems, we proposed applying a nonlinear optimization method based on foraging behavior of bacteria known as BFO algorithm, to fit the BIS data to the Cole function. We employed simulated datasets to test the parameter extraction accuracy and noise sensitivity of the BFO algorithm and used the LS fitting for comparison purpose. The fitting results showed that while the LS fitting performance is deteriorated by noise, the BFO fitting method shows high robustness to the added noises. We also presented the results of a classification task on the experimental data obtained from forearm bioimpedance measurements in three different arm positions and used GA and PSO algorithm for comparison purpose. The extracted feature sets by LS, BFO, GA and PSO fitting methods were used as the input to different types of classifiers; first by applying the classification task on training data and then on test data using the cross validation method. The feature sets by BFO showed better classification accuracy and higher ability in prediction of the test data. The classification performance of the PSO algorithm was also close to the BFO algorithm and they both had a better classification performance than GA.

In terms of the required execution time, the LS method was more efficient than the BFO fitting method. While LS had a average execution time of 0.78 s, the average execution time was 25.4, 28.2 and 21.7 s for BFO, PSO and GA algorithms. The execution time are obtained by running the code in Matlab on Intel(R) Core(TM) i5-4310U processor with 16GB of memory. This might limit using the BFO fitting method in some real-time applications where the execution time is of primary importance. However, the promising point is that the real-time performance is not usually critical in our application, because in BIS applications the number of measurements is usually set beforehand, and processing the data is done after all the measurements are collected. As future works, developing some modifications on the original BFO algorithm should be investigated to increase its efficacy for implementations in online BIS applications.

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