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Lung Sounds Signal Separation Model of Medical Monitoring Based on Wireless Sensor Network

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Abstract

According to the present medical monitoring system still exist the problems such as low accuracy of the condition judgment and the less range of data transmission, a kind of lung sounds signal separation model of medical monitoring is put forward based on wireless sensor network. First, using the optimization strategy of the flying speed and the effect between particles to two-way optimization for particle swarm optimization algorithm (PSOA), and then applied it to the blind source separation of lung sounds signal, in order to improve the precision of the blind source separation of lung sound signals, then carried on the optimization of artificial fish behavior through tabu search, did coverage optimization for wireless sensor network by using the improved algorithm, to expand the scope of wireless data transmission. As the simulation experiments results showed that, the proposed lung sounds signal separation model of medical monitoring based on wireless sensor network had good accuracy and large range of data transmission, and deserved to be popularized and used.

Keywords: *Improved Particle Swarm Optimization Algorithm (PSOA), Wireless Sensor Network, Medical Monitoring, Lung Sound Signals Separation, Blind Source Separation, Tabu Search, Behavior Optimization of Artificial Fish*

1. Introduction

The great advantage of lung sound in the diagnosis of disease is that is no harm to human body, and it contains a lot of information in lung sounds, all sorts of human diseases are reflected in lung sound that we have not master the law yet [1]. Heart, lung, brain and other organs of our body keep moving with all kinds of sound signals time to time, these signals are the active physiological sound signals. In addition, when the body has some kind of action imposed from outside, or a part of the human body to exert some effect on another part, can produce passive physiological sound signals, such as sounds of muscles, sounds of joints, sounds of transmission, sounds of percussion and so on [2]. To provide new non-invasive diagnostic method for clinic, we need to adopt new theories and methods to extract and identify the acoustic information of human organs and then find out the rules for clinical diagnosis and treatment methods with non-invasive; these kinds of researches have important application value and theoretical significance.

At present, for the separation of lung sound signals, uses basically is blind signal separation technology, domestic and foreign experts and scholars have conducted some research on the technology. For mixed two linear source signals, Jutten proposes H-J recursive neural network, and realizes the blind source separation [3]. Comon proposes unified framework of independent component analysis (ICA) and the basic assumptions

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of separation problem based on the independent blind signal, He points out that should make the objective function optimization through the establishment of an objective function, so as to realize the related of observation signal, realizes the blind source separation of signal on this basis [4]. Based on information maximization principle, Bell puts forward the famous entropy maximization of blind signal separation algorithm [5]. Amari and others improve entropy maximization algorithm, this method overcomes the problem that the entropy maximization algorithm need to compute inverse matrix, so that to improve the stability of the algorithm and reduces the computational complexity [6]. Cardoso and others put forward relative gradient algorithm, compared with the traditional entropy maximum algorithm, it avoids the separation matrix inversion, and significantly improves the stability of the algorithm [7]. Peadmutter and others to promote the traditional entropy maximization algorithm, get the maximum likelihood estimation separation algorithm of blind signal, this method implements the maximum likelihood estimation algorithm of online parameters by using multivariate density maximum likelihood theory, which can expand the scope of separate source signals type [8]. Lee and others analyze the problems of nonlinear functions fixed by maximum entropy separation algorithm of blind signal, analyze the difference of nonlinear function of super-Gaussian signal and sub-Gaussian signal, choose different evaluation function in the algorithm, can realize blind source separation of super-Gaussian and sub-Gaussian mixed signal [9]. Hyvarinen and others propose Fast ICA algorithm, namely fixed point of learning algorithm, the great advantages of this algorithm is convergence speed, so it is widely used in practical applications [10]. In addition, Oja and XU Lie introduce nonlinear function in the principal component analysis method at the earliest, put forward the concept of nonlinear principal component, and apply it successfully in the separation of blind signal [11]. Yu Xiao proposes a kind of separation algorithm of the maximum entropy blind signal, which enhanced by the estimation of a mixed signal probability density function, and applies the algorithm in the field of language signal recognition [12]. Zhang Liqing and others put forward the theory and method of adaptive separation of blind signal, better solve the problems such as natural gradient in instantaneous mixture model of non-square matrix, geometric properties of the hybrid model of the signal blind deconvolution, and apply it to the brain signal analysis and processing [13]. Wu Xiaopei applies blind signal separation to pre-processing of EEG signals, isolate noise in EEG signals [14].

Based on wireless sensor network, we propose a lung sound signal separation model of medical monitoring, optimize the blind signal separation algorithm by using particle swarm algorithm with two-way optimization, to improve its accuracy in the lung sound signals separation, and use the tabu artificial search and its algorithm to increase the transmission range of wireless sensor network.

2. Lung Signal Separation Based on Improved Algorithm of Blind Source Separation

In the proposed lung sound signals separation model of medical monitoring, which based on wireless sensor network, first improve lung sound signals separation technology on basis of blind signal separation algorithm number.

2.1. Mathematical Model of Blind Signal Separation

With Assumed that the number of source signals exactly as same as the number of observed signals, the mathematical model of blind source separation is shown in Figure 1.

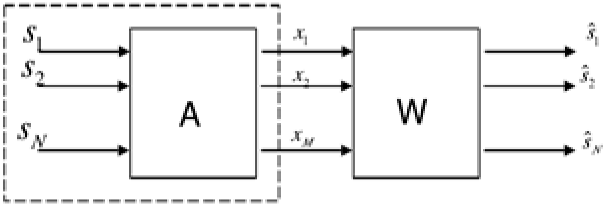

Figure 1. Blind Signal Separation Model

In Figure 1, it has N numbers of source signals $s_i\,(i = 1, 2, ..., N)$ in dotted box, the source signals and a mixture of relationship between them namely mixed matrix A is unknown. Currently the known observed signal is only M samples with the same length $x_i\,(i = 1, 2, ..., M)$. Seen form Figure 1,

$$x_i(t) = As_i(t), i = 1, 2, ..., N \tag{1}$$

The observed signals vectors of dimension represented by m , the source signals vectors of n dimension represented by s_i . Each component of source signal must satisfy the conditions of mutual statistical independence, constant confusion matrix A has dimension $m \times n$, and satisfy the conditions of column full rank. The result of blind source separation process is to make the output signal $\hat{s}_i$ close to the real source signal as much as possible, namely,

$$\hat{s}_i(t) = B\Lambda s_i(t) \tag{2}$$

In equation (2), represents as any replacement array, represents as any nonsingular diagonal matrix. Create a matrix W , and then get equation (3).

$$\hat{s}_i(t) = Wx_i(t) = WAs_i(t) = B\Lambda s_i(t) \tag{3}$$

The difference of source and estimate signals only performance on the order and amplitude values of each component, which can be thought that estimate signals is a copy of the source signals. Blind source separation algorithm by looking for separation matrix W , also called solution mixing matrix.

2.2. Blind Signals Separation Based on Improved PSO

To improved accuracy and convergence precision of particle swarm algorithm in blind signals separation, we make it for the two-way optimization.

2.2.1. Optimize the Flight Speed

According to the end of particle PSO, the slow speed of flight, which results in the phenomenon of the stagnation of global search, we proposes a way to help the algorithm in a timely jump out of local optimal solution when appears premature phenomenon, to ensure the diversity of particle population, to enhance the search precision of PSO.

First, set a threshold value D for algorithm, and

$$D = \frac{P_{gD}}{\frac{1}{n}\sum_{i=1}^{n} P_{iD}} \tag{4}$$

In equation (4), P_{gD} represents as the globally optimal solution of population in d dimension; P_{iD} represents as the individual optimal solution of number i particle in d dimension; n represents as the size of the population.

So in $0 < D \leq 1$, and the greater the D is, the more concentrated the population of particles are, and more easy to fall into local optimal solution. Set a maximum $D_{\max}(0 < D_{\max} < 1)$ for threshold value D, when $D \geq D_{\max}$, makes part of the particles to initialize particles in population.

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So after start the particle swarm search, if the population of particles were concentrated towards a search region, the algorithm loses the diversity of the population, and makes the PSO algorithm in local search and can't jump out to search the global optimal solution. At that time in the iteration process of algorithm can automatically calculate the size of the threshold value D, namely the threshold value D is bigger and bigger. Once $D \geq D_{\max}$, algorithm can automatically randomly initialize part of particles in population. Thus the initialized particles can jump out of local optimal predicament, to have the global search ability, to ensure the diversity of particles population, in order to search for better global optimal solution.

2.2.2. Optimize the Effect between Particles

We improved the equation of basic PSO, and get the new equations (5) and (6).

$$\begin{aligned} v_{iD}^{t+1} = w v_{iD}^{t} + c_1 r_1 (p_{id} - x_{iD}^{t}) + c_2 r_2 (p_{gd} - x_{iD}^{t}) \\ + c_3 r_3 (p_{jd} - x_{iD}^{t}) \end{aligned} \tag{5}$$

$$x_{iD}^{t+1} = x_{iD}^{t} + v_{iD}^{t+1} \tag{6}$$

In equation, p_{jd} represents as individual optimal solution of any random particle, which except particle i.

Through these two improvement, not only let the basic PSO algorithm to well overcome the problem of premature phenomenon that easy to fall into local optimal solution, and also increases the contacts between particles in algorithm, let the PSO algorithm has a faster and more accurate search capabilities in the process of later local optimization, not only strengthen the convergence speed in the later PSO, as well as enhances its convergence precision.

According to separation model of blind signal, the improved PSO is applied to the blind source separation of lung sound signals.

$$x(z) = H(z)s(z) \tag{7}$$

$$y(z) = W(z)x(z) \tag{8}$$

According to the blind deconvolution of equation (7) and (8) on frequency domain is similar to the instantaneous mixture blind source separation on time domain, the process of separation is to determine $W(z)$.

Optimize the flight speed. According to the end of particle PSO, the slow speed of flight, which results in the phenomenon of the stagnation of global search, we proposes a way to help the algorithm in a timely jump out of local optimal solution when appears premature phenomenon, to ensure the diversity of particle population, to enhance the search precision of PSO.

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3. The Coverage Optimization of Medical Monitoring Model Based on Wireless Sensor Network

After establish lung sound signals separation model of blind separation algorithm based on PSO, transmit the signals by wireless sensor network, to achieve the purpose of medical monitoring, but wireless sensor network has low coverage at present, so we optimize it.

3.1. The Behavior Description of the Artificial Fish Swarm Algorithm (SFSA)

Through the study we found that the AF-prey, AF-swarm, AF-follow and AF-random of fish swarm have a very close relationship with the solution of the optimization problem.

3.1.1. AF-Prey

Set the current status of artificial fish as X_i, randomly select a state X_j in the visible domain (namely $d_{i,j} \leq Visual$), if the food concentration of this state Y_j is higher than current state Y_j (the following adopts the maximum optimization for example), then X_j moves a step forward; otherwise, randomly select state X_j again, and determine whether meets the conditions of forward; after try over and over again. Try several times, if the new state still doesn't meet the conditions, then move a step randomly. The mathematical equation (9) of next selected state is as follows,

$$\begin{cases} x_{inextk} = x_{ik} + Random(Step)\dfrac{x_{jk} - x_{ik}}{\| X_j - X_i \|}, Y_j > Y_i \\ x_{inextk} = x_{ik} + Random(Step), Y_j \leq Y_i \end{cases} \tag{9}$$

In equation (9), $k = 1, 2, \ldots, n$, x_{jk}, x_{ik} and x_{inextk} represent as state vector X_j and X_i, and number k element of next state vector x_{inext} of artificial fish respectively,

$Random(Step)$ represents as random number on $[0, Step]$, Y_j and Y_i as state, X_i and X_j as corresponding food concentration. The following kinds of symbolic meanings are as same.

3.1.2. AF-Swarm

Set the current state of artificial fish as X_i, discover the number of partners n_j and central position X_c in the current field, if $Y_c / n_f > \delta Y_i$ (Y_c as food concentration of partners central position), shows that it has a higher food concentration in partners centre, and not very crowded, and then move a step to the centre position of partner's direction, otherwise perform AF-prey (AF-prey sets as default behavior).

Set the current state of artificial fish as X_i, the number of partners in the visible domain is n_f, form a set KJ_i,

$$KJ_i = \{X_j \| \|X_j - X_i\| \le Visual\} \tag{10}$$

If $KJ_i \neq \phi$, and meets cluster condition, then move to the next state of the partners centre position, the mathematical equation (11) as follows.

$$x_{inextk} = x_{ik} + Random(Step)\frac{x_{ck} - x_{ik}}{\|X_c - X_i\|} \tag{11}$$

In equation, x_{ck} represents as number k element of state vector X_c.

If $KJ_i \neq \phi$, means there is no other partners in visible domain, then perform the AF-prey (AF-prey sets as default behavior).

3.1.3. AF-Follow

In the process of fish swimming, when one or several found food, their neighboring partners following them to the food store, this is follow behavior.

Set the current state of artificial fish as X_i, discover the number n_f of in current neighborhood (namely $d_{i,j} \le Visual$) and the biggest $X_{\max}$ in partners $Y_{\max}$, it means partner $X_{\max}$ has a higher food concentration and not very crowded, and then move a step to the centre position direction of partner $X_{\max}$, otherwise perform AF-prey.

Mathematic equation (12) of moving to the direction of partner $X_{\max}$ is as follow,

$$x_{inextk} = x_{ik} + Random(Step)\frac{x_{\max k} - x_{ik}}{\|X_{\max} - X_i\|} \tag{12}$$

In equation, $x_{\max k}$ represents as number k element of state vector $X_{\max}$.

3.1.4. AF-Random

AF-random is that artificial fish randomly select a state in the field of vision scope, and then swim to the direction, which is looking for a wider range of food or companion.

3.2. Optimize the Coverage of Wireless Sensor Network Based on Improved Artificial Fish Swarm

Optimize the artificial fish behavior by tabu search, if found that the state of artificial fish X_j was already in tabu list (namely algorithm was used to through the state), we need to consciously avoid this status, and get the new artificial fish vector based on tabu calculation. For the current state X_i of artificial fish and the new calculated state X_j, tabu calculation equation is as follows,

$$X_{new} = X_i + \eta(X_j - X_i) \tag{13}$$

In equation, $0 < \eta < 1$, is a random number. "$-$" means the comparison of each dimension of component between two vectors X_i and X_j, "$+$" means complete the substitute of X_i. The whole meaning of the equation is: operate the substitute of different component with η probability in artificial fish X_i and X_j and the same components maintain same.

3.2.1. Optimize the AF-Prey

Improve random AF-prey by using tabu algorithm, while maintaining the global optimization ability of the algorithm, reduces the number of indirect search. AF-prey process is as follows,

Step1: artificial fish X_i randomly find the next state in the field of vision,

$$X_{inext} = X_i + Random(Visual) \tag{14}$$

Equation (4) means artificial fish select $Visual$ components randomly, with 0/1 inversion.

Step 2: if $F(X_{inext}) < F(X_i)$, turn to step 3; otherwise generate X_{new} according to equation (8), and judge X_{new} whether is in tabu list, if it is not in tabu list or in the tabu list but ignore the rules, then use X_{new} to replace X_i, and update the tabu list. Turn to step 3.

Step 3: test a new state in the field of vision again, then turn to step 2. Such repeated several times to retry count, if it still does not meet the conditions of forward, then random walk $Step$ steps.

$$X_i = X_i + Random(Step) \tag{15}$$

3.2.2. Optimize the AF-swarm

AF-swarm is that each artificial fish swim as far as possible to the center of the neighbor fish swarm and avoid overcrowding in the process of moving.

Step 1: first, artificial fish search neighborhoods within their field of vision, compute its total number n_f, and neighbors fish matrix, and compute the center of neighbors X_{i_c} according to equation (16) (if get same times of some dimensional time component which is 0 or 1 for operation of neighbors center $most$).

$$center(X_i) = \underset{j=t,t\_1,\ldots,1\_n}{most}(a_{j1}, a_{j2}, \ldots, a_{jN}) \tag{16}$$

In equation, $most$ operator means more occurrences component values of each column in fish matrix.

Step 2: if food concentration is higher and not too crowded in neighbor center position, namely meets the conditions $F(X_{i\_c}) > F(X_i)$ and $n_f / NF < \delta$, then to move a step towards the neighbor center.

AF-follow is that behavior $X_{i\_\max}$ of artificial fish chasing and catching the largest food concentration in their field of vision, if it is not too crowded around, artificial fish move a step toward the direction.

4. The Performance Simulating of Algorithm

In order to verify the effectiveness of the proposed improved algorithm, simulation experiments are performed. First using the Sphere function to verify the convergence of the improved PSO, Sphere function as equation (17), the result is shown in Figure 2.

$$f_1(x) = \sum_{i}^{n} x_i^2 \tag{17}$$

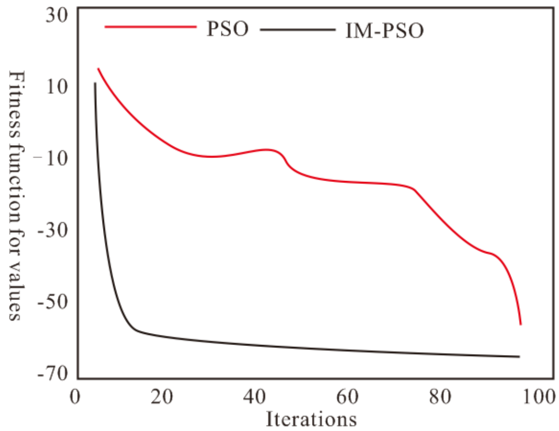

Figure 2. The Compare Results of Optimization Process of Sphere Function

It can know that, compared with the original PSO algorithm, the proposed improved PSO algorithm has the faster search speed, low volatility, and easier to achieve the optimal value.

Then verify the blind signals separation model based on the improved PSO algorithm, Figure 3 is the observed lung sound signals, and Figure 4 is lung sound signals of separation.

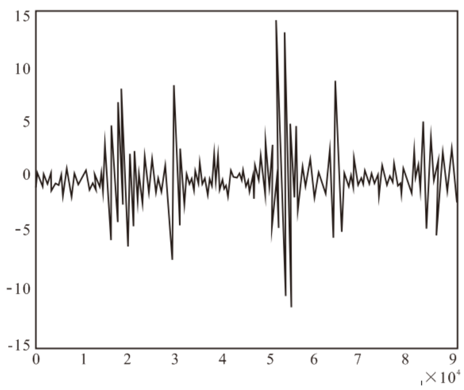

Figure 3. The Observed Lung Sounds Signals

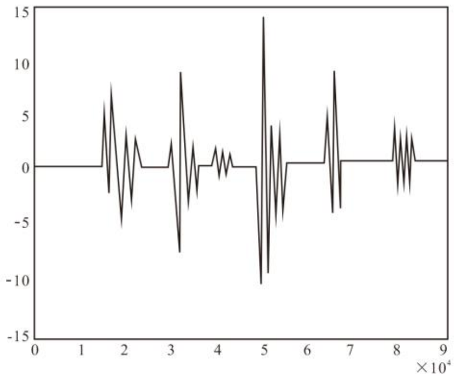

Figure 4. The Separated Lung Sounds Signals

As shown in Figure 3 and Figure 4, the acquisition of lung sound signals can be well separated by blind signals separation model based on improved PSO.

Finally, perform the simulation for coverage optimization strategy of wireless sensor network, the results are as follows.

Table 1. The Comparison Results of Node Scheduling Time

Iteration time	Improved algorithm coverage	Standard algorithm coverage	Improved algorithm nodes	Standard algorithm nodes
100	82.87	19.27	63	65
120	86.84	84.12	60	62
140	90.14	87.18	57	60
160	94.25	90.53	55	58
180	96.86	91.28	55	56
200	98.46	93.57	55	55

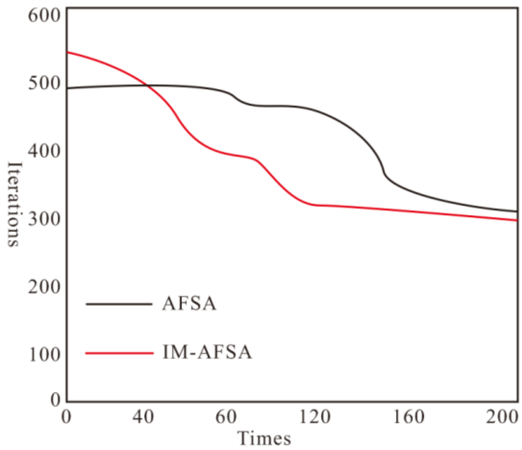

Figure 5. The Comparison Results of Convergence

The simulation results show that, the proposed lung sound signal separation model of medical monitoring based on wireless sensor network has better accuracy and large range of data transmission.

5. Conclusions

Lung sounds is one of the most important physiological acoustic signals of body, and is a result for breath sounds generated in the respiratory system, contains physiological and pathological information of the lungs. At present, the analysis of lung sound signals is still one of the main diagnostic methods of respiratory disease. Seen from the simulation results, the proposed the lung sound signal separation model of medical monitoring based on wireless sensor network has higher accuracy and larger range of data transmission, and is conducive to real-time medical monitoring of patient.

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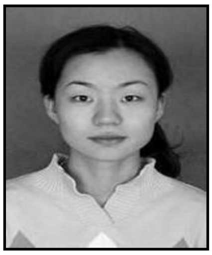

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