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AN IMPROVED NONINVASIVE AND MULTIMODEL PSO ALGORITHM FOR EXTRACTING ARTIFACTS FREE FOETAL ECG

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Abstract: In this paper, the non-invasive methodology for removing Fetal Electrocardiogram (FECG) is gained by subtracting the balanced variation of maternal electrocardiogram (MECG) movement from the abdominal electrocardiogram (AECG) banner. The banner assessed from the mother's guts (AECG) is regularly overpowered by maternal heartbeat. The maternal portion of the AECG is the nonlinearly changed variation of MECG. This paper uses an Adaptive Neuro-Fuzzy Interference System (ANFIS) structure. It is used for finding the non-direct change and the ensuing banner are set up with people based request figurings. This strategy involves some specific issues which are a direct result of the low force of the fetal ECG which is sullied by various wellsprings of checks. It joins maternal ECG, electromyogram (EMG) signals, power line impedances and sporadic electronic upheavals. Along these lines, we are proposing an improved multimode PSO estimation for overcoming this issue. In addition, methods like wavelet change, flexible filtering, thresholding are moreover used. We have furthermore empowered the thoracic and stomach signals using MATLAB programming. It uses only two signs recorded at the thoracic and stomach regions of mother's skin. Similarly, our test shows that the proposed count can expel FECG banner immediately in pregnancy period and that is one of the basic focal points of figuring.

Key words: FECG, fetal ECG, AECG, MECG.

I. INTRODUCTION

In the current technique, the non-intrusive strategy for extricating fetal electrocardiogram (FECG) is acquired by subtracting the adjusted variant of maternal electrocardiogram (MECG) motion from the stomach electrocardiogram (AECG) flag. The flag estimated from the mother's guts (AECG) is normally overwhelmed by maternal heartbeat.

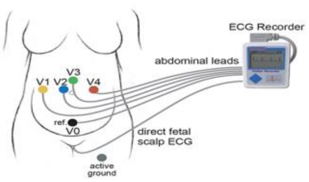

Fig1. Recording Abdominal ECG Signal

The maternal segment of the AECG is the nonlinearly changed variant of MECG. This paper utilizes an Adaptive Neuro-Fuzzy Interference System (ANFIS) structure. It is utilized for finding the non direct change and the subsequent flag are prepared with populace based inquiry calculations. This technique comprises of some specialized issues which are because of the low intensity of the fetal ECG which is sullied by different wellsprings of obstructions. It incorporates maternal ECG, electromyogram (EMG) signals, powerline impedances and irregular electronic commotions. So we are proposing an improved multimode PSO calculation for defeating this issue. What's more, procedures like wavelet change, versatile sifting, thresholding are additionally utilized. We have additionally invigorated the thoracic and stomach signals utilizing MATLAB programming. It utilizes just two signs recorded at the thoracic and stomach territories of mother's skin. Likewise, our test demonstrates that the proposed calculation can remove FECG flag right off the bat in pregnancy period and that is one of the critical advantages of calculation.

II. RELATED WORKS

2.1 EXISTING METHODS

Here the foetal ECG's are extracted by ANFIS(Adaptive Nero Fuzzy Interference System) trained with PSO algorithm. Generally, the maternal component of the abdominal ECG signal is the non-linearly transformed version of the MECG. This nonlinear transformation is determined by using ANFIS.

ANFIS architecture requirements and initializations are fewer and simpler in comparison with neural networks which require so many trials and errors for optimized updating the weights.

ANFIS structure:

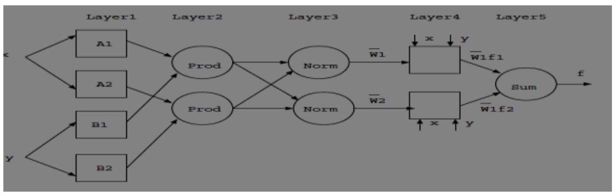

Figure 2. First order sugeno fuzzy model

2.2 ANFIS Training

It is trained by using PSO. The PSO algorithms are a population based search algorithms based on the simulation of the social behavior of birds within a flock. In PSO algorithm the velocityis adjusted according to its own flying experience.

2.2.1 ALGORITHM

1. Initialize the swarm, p(t), of particles such that the position xi^(t) of each particle will be random within the hyperspace, t=0
2. Evaluate the performance F of each particle, using its current position xi^(t)
3. Compare the performance of each individual to its best performance:
   If
   $$F(\vec{x}_i(t)) < pbest$$
   Then
   $$\begin{cases} pbest_i = F(\vec{x}_i(t)) \\ \vec{x}_{pbest_i} = \vec{x}_i(t) \end{cases}$$
4. Compare the performance of each individual to global past particle:
   If
   $$F(\vec{x}_i(t)) < gbest$$
   Then
   $$\begin{cases} gbest_i = F(\vec{x}_i(t)) \\ \vec{x}_{gbest_i} = \vec{x}_i(t) \end{cases}$$
5. Change the velocity vector for each particle using the equation
   $$\vec{v}_i(t) = \vec{v}_i(t-1) + \rho_1\left(\vec{x}_{pbest_i} - \vec{x}_i(t)\right) + \rho_2\left(\vec{x}_{gbest} - \vec{x}_i(t)\right)$$
   Where p1 and p2 are random variables
6. Move each particle to its new position using the equation
   $$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t)$$
7. Go to step 2 and repeat the algorithm until the convergence is reachedThe random variables p1 and p2 , defined as p1=r2c2 and p2=r1r2~U(0,1). C1, C2 are positive acceleration constant. It has been shown that if c1+c2<=4 then the stability of PSO is guaranteed.

III METHODOLOGY

3.1 PROPOSED METHOD

We are proposing two methods for extracting FECG from the signals recorded at the mother's abdominal region.

The first method is the IMPROVED MULTIMODE PSO ALGORITHM and the other is the combination of ADAPTIVE FILTERING, WAVELET TRANSFORMATION andTHRESHOLDING.

For evaluating the performance of the proposed algorithm, we have also stimulated the thoracic and the abdominal ECG signals using MATLAB software.

3.2 IMPROVED MULTIMODE PSO ALGORITHM

The drawback obtained in the PSO algorithm is eliminated by the improved multimode PSO algorithm. In this method, the values for the ECG signal are taken for both in time and frequency plot. Here both the particle's position and velocity are determined accurately. This method segments the continuous signal so that it is easy to define their velocities. The FECG signals which are extracted from this method are of high power.

It requires only two signals for the extraction of foetal ECG which are recorded at the mother's abdomen and thoracic areas.

3.2.1 Introduction

PSO is one of the famous evolutionary computation'stechniques introduced by Kennedy and Eberhart in1995[1]-[2]. It is a population-based search algorithmwhich is initialized with a swarm of random particles.PSO makes use of a velocity vector to update thecurrent position of each particle in the swarm underthe rules: (1) maintaining own inertia; (2) using ownpersonal best solution and (3) based the global bestsolution. The velocity vector is updated based on thehistory information gained by the swarm. And thepositions of the swarm are updated to search for betterpositions according to the updated velocity vector [3].In our early work, a new PSO algorithm, called θ-PSOwas put forward [4]. In θ-PSO, increment of phaseangle vector θ rΔ replaces velocity vector *vr* and thepositions are adjusted by the mapping function ofphase angles. Benchmark testing of nonlinearfunctions shows that θ-PSO appears to be a promisingapproach of function optimization. But this algorithmmay easily stick in the local minima when handlingsome complex or multi-mode functions such as Acklyand Rastrigrin etc. In this paper, an improved θ-PSOalgorithm with mutation operator is studied. And thisimproved algorithm has better optimizationperformance when solving some complex functions.Experiments results show that this improved θ-PSOcan overcome the local minima and achieve the goalof global minimum in limited iterations.

3.3 Improved θ-PSO algorithm

Compared to basic PSO algorithm, θ-PSO algorithmhas better optimization performance when dealingwith some simple benchmark functions [1]. But it'sdifficult for basic θ-PSO algorithm to overcome thelocal minima when handling some complex or multimodefunctions. So in this paper, we adopt themutation operator of genetic algorithm. If the personalfitness value has not improved compared the lastiteration's result, i.e., if *Fi* (*t*) >*Fi* (*t* −1) , a mutationoperator is introduced in the basic θ-PSO algorithmwith a small probability. And the detail is as follow: if*Fi* (*t*) >*Fi* (*t* −1) , create a random number *dij*∈(0,1) ,if *dij*<*Pm* , do

$$\theta_{ij}(t) = -\theta_{ij}(t) + c_3 * (\vec{r}_3(t) - 0.5)$$

where *Pm*∈[0,1] , 3 *c* is a non-negative real number,*r*3 (*t*) r ~ *U*(0,1) , and limit θ*ij*to

(π/2, -π/2). In thispaper, a minus value of θ*ij*is adopted because therange of phase angle is symmetrical. Simulationresults show that the added disturbance item*c*3 *(*r*3 (*t*) − 0.5) r is effective sometime.

The improved θ-PSO algorithm can besummarized as follow:

1) Create and initialize a *n* -dimensional swarm(phase angle) 1 (*I* θ r) and *I* θ rΔ(1) ;

2) *t* =1, calculate *xi* (1) r using Eq.(3), calculate thefitness value *Fi* (1) using Eq.(4) and set $F_{ib}(1) = F_i(1)$, *Fg*(1) = min *Fi* (1) ,and set θg(1) equal to the panes anglescorresponding to min *Fi* (1) ; Then set *t* = 2 ;

3) Update $\Delta\vec{\theta}_i(t)$ using Eq. (1), and limit $\Delta\vec{\theta}_i(t)$ to $(\Delta\theta_{\min}, \Delta\theta_{\max})$;

4) Update $\theta_i(t)$ using Eq. (2), and limit $\theta_i(t)$ to (θmin ,θ max) ;

5) Update *xi* (*t*)r using Eq. (3);

6) Calculate *Fi* (*t*) using Eq. (4);

Function	Minimum value of fitness value	Maximum value of fitness value	Average value of fitness value
Rosenbrock	11.8792	19.7983	16.5436
Rastrigrin	87.4972	151.2327	134.8754
Schwefel	1189.6	1437.9	1263.9
Ackly	17.8285	19.7033	18.8354

Table 1: Test results of standard θ-PSO

IV. SIMULATION RESULTS

The signal displayed below is the normal ECG signal recorded from the abdomen portion having

a = 0.0350

u1 = 2.4000

u2 = 0

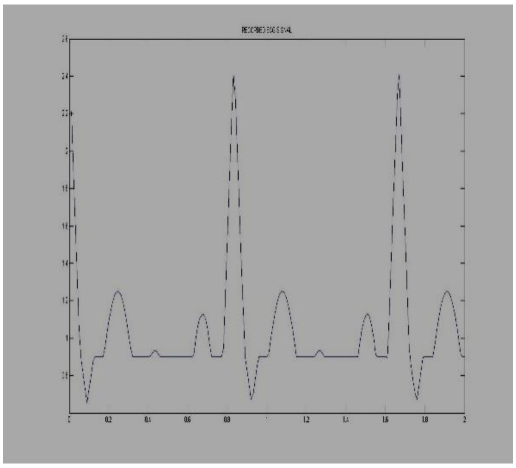

Fig:3 Recorded ECG signal (Input)

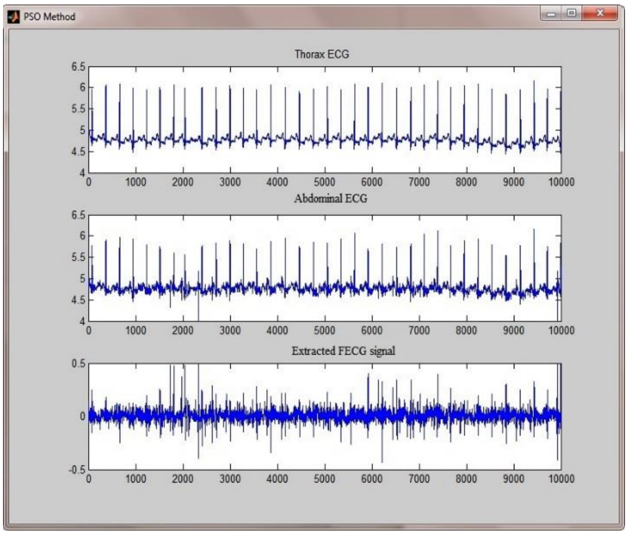

Fig:4 PSO Method

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V. CONCLUSION

The movement relic brought about by subject movement just as by physical movement of body parts has a changing recurrence which may lies in a similar scope of the flag recurrence. It is hard to channel clamor from these signs utilizing customary channels, and blunders coming about because of separating can contort them and doctors may misdirect by these boisterous signs and this may make the finding unrealistic or an incorrect analysis is the outcome. By serious consideration and crisis the nonstop enhancement of tissue with the oxygen is pivotal (particularly cerebrum tissue, where following couple of minutes oxygen lack causes irreversible harm of tissue). The computation of oxygen immersion by heartbeat oximetry depends on photoplethysmography and photospectroscopy.It will likewise drastically diminish the unsettling influences (alert) for patient and therapeutic consideration stuff, lessen expenses and upgrade the medicinal frameworks.

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