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Research Article

Optimization of UWB Receiver using the Improved Memetic Algorithm in WBAN

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Abstract: A novel method for Ultra Wideband (UWB) receiver design in Wireless Body Area Network (WBAN) is proposed in this study. The method is based on the Improved Memetic-Algorithm (IMA), with the output Signal-to-Noise Ratio of the receiver (SNR_{out}) is optimized. By relating the target SNR_{out} to the parameters of main components, including Low Noise Amplifier (LNA), mixer and base-band Low Pass Filter (LPF), an objective function was built for multi-parameters optimization in the IMA. The optimum values of small signal gain, noise factor and inter-modulation product can then be calculated. Two PSO algorithms, CLPSO (Comprehensive Learning Particle Swarm Optimizer) and AdpISPO (Self-adaptive Intelligent Single Particle Optimizer) were introduced in the IMA for different particles updating. The proposed method was validated through extensive experiments. Comparing to conventional PSO approaches, the proposed method can converge to the optimum design with less iteration.

Keywords: ADS simulation, memetic algorithm, PSO, ultra wideband receiver, wireless body area network

INTRODUCTION

Wireless Body Area Network (WBAN) is a typical interdisciplinary of bioelectronics, sensors and wireless communication. In recent years, there has been increasing interest in using Ultra Wideband (UWB) wireless technology for WBAN applications and numerous UWB based WBAN designs, such as telemedicine (Wong *et al*., 2008), neural recording (Yuce *et al*., 2009a) and electronic pill (Yuce *et al*., 2009b), have been published. An UWB-based WBAN system consists of multiple sensor nodes and a single UWB-receiver node attached to each user (Henrik *et al*., 2005). A typical block diagram of the UWB receiver circuit is shown in Fig. 1 (Keong *et al*., 2010). The received RF signal first passes through a 3 to 5 GHz band-pass filter (BPF) and is amplified by a wideband Low-Noise Amplifier (LNA). The amplified RF signal is then down-converted to baseband signal through a mixer and a 100 MHz Low-Pass Filter (LPF) is utilized to block the out-of-band noise and interference.

In UWB receiver design, it is critical to calculate the key parameters of the LNA, the mixer and the LPF in order to obtain optimum systematic performance. However, traditional design way depends largely on experience and the design process inevitably includes numerous repeated calculations and verifications steps. In order to improve design efficacy, multi-parameter optimization algorithms, such as Memetic Algorithm (MA), could be utilized. MA is a hybrid biological heuristic optimization method framework (Moscato, 1999) and has already been adopted successfully in many electronic system designs, such as OFDM mobile communication system (Jiang and Hanzo, 2010) and passive filter design (Bogale *et al*., 2012).

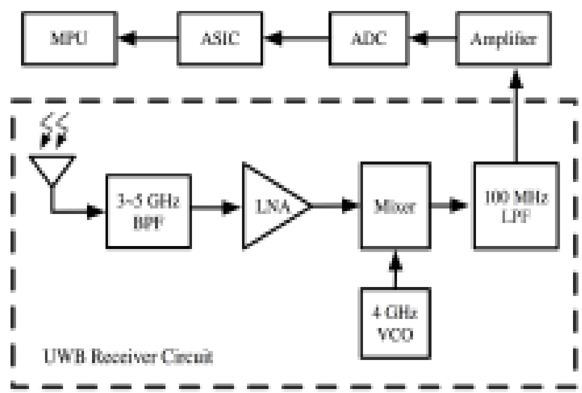

Fig. 1: Block diagram of the UWB receiver circuit

In this study, in order to calculate the optimum values of the key parameters of the UWB receiver in WBAN applications, a novel systematic optimization method based on the Improved-MA (IMA) is proposed. An objective function targeted for the output optimum signal-to-noise ratio of the receiver (SNR_{out}) is used for multi-parameter optimization in the IMA. Two representative PSO algorithms, CLPSO

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(Comprehensive Learning Particle Swarm Optimizer) algorithm (Liang *et al*., 2006) and AdpISPO (Self-adaptive Intelligent Single Particle Optimizer) algorithm (Zhou *et al*., 2010) are introduced in MA framework to improve the algorithm efficiency.

In experiments, a comparison between the IMA and other conventional PSO optimization approaches is given to show the efficiency of the proposed algorithm first. Second, after obtaining the optimum values of the key parameters by the proposed method, the performance of the UWB receiver is validated in Advanced Design System (ADS) (Roslee and Subari, 2010).

IMPROVED MEMETIC ALGORITHM

Various Particle Swarm Optimization (PSO) algorithms are able to explore and exploit the promising regions in search space, but the searching process take relatively long time. Hence, algorithms are hybridized for utilizing better exploration and exploitation capacities to make the algorithm faster while keeping its accuracy. The CLPSO algorithm and the AdpISPO algorithm are combined in the IMA for different particle swarms updating. As the global search tactics, in the CLPSO, the velocity V and position P of the k^{th} dimension of the i^{th} particle are updated as follows:

$$V_i^{k+1} = w_k \times V_i^k + c \times r^k \times (pbest_i^k - P_i^k) \quad (1)$$

$$P_i^{k+1} = P_i^k + V_i^{k+1} \quad (2)$$

where, $pbest_i$ is the best previous position yielding the best fitness value for the i^{th} particle c is the acceleration constants reflecting the weighting of stochastic acceleration terms that pull each particle toward $pbest_i$; r is a random number in the range [0, 1].

By using a novel learning strategy whereby all other particles' historical best information is used to update a particle's velocity, the CLPSO can achieve a good performance in global search, but have limited ability in local search.

Therefore, the AdpISPO algorithm is introduced for optimization in local search. To overcome the drawback of overly dependence on input parameters in the ISPO (Ji *et al*., 2010), the AdpISPO can achieve better performance in local search with no critical parameter required. The update functions of the AdpISPO are given in Eq. 3 and 4:

$$\begin{aligned} V_j^{k+1}[d] = w \times V_j^k[d] + c_1 \times r_1 \times (pbest_j[d] \\ - Y_j^k[d]) + c_2 \times r_2 \times (gbest_j[d] - Y_j^k[d]) \end{aligned} \quad (3)$$

$$Y_j^{k+1}[d] = Y_j^k[d] + V_j^{k+1}[d] \quad (4)$$

V = The velocity
$Y = [A, P]$ = A new vector of the position P and the key parameters of the ISPO A combination
w, c_1 and c_2 = The acceleration constants and $w = 0.5$, $c_1 = c_2 = 2$ are set in this study
$pbest_j$ = The best previous position yielding the best fitness value for the j^{th} particle
$gbest_j$ = The best previous position yielding the best fitness value for the swarms

A weighted roulette tactics is used in the IMA. First, the particles are divided into leader particles and populace particles by their fitness values. Second, because the leader particles are close to the global best position, the AdpISPO is used for their updating to accelerate the convergence. For the populace particles, one of three tactics can be chosen: *Approaching*, *Random* and *Dispersa*. It is used for particles updating by the trend of their fitness values. Therefore, a descent rate of fitness values δ is defined as follow:

$$\delta = 1000 \times \frac{(lastvalue - fitness(gbest))}{lastvalue} \quad (5)$$

fitness() is the fitness function;
lastvalue is the fitness value of the last iteration.

When $\delta \geq 10$, the fitness values decreases rapidly and the position is close to the global best position. The weight for the Approaching tactics should be increased to make more particles search near current position in next iteration. The update formula of Approaching tactics is:

$$P_i^{k+1} = P_i^k + (gbest^k - P_i^k) \times r \quad (6)$$

When $1 \leq \delta < 10$, there is a slow drop of the fitness values, which means that the swarm haven't been able to locate the global best position. The weight for the Random tactics should be increased to expand the search scope. Its update formula is:

$$P_i^{k+1} = rand(P_{\min}, P_{\max}) \quad (7)$$

$[P_{\min}, P_{\max}]$ is the range of particle position vector.

When $\delta<1$, the descent of fitness values tend to be stop, the current position may be the global minima, or local minima. In order to avoid premature convergence, the weight for the Dispersal tactics should be increased. Its update formula is:

$$P_i^{k+1} = P_i^k - (gbest^k - P_i^k) \times r \quad (8)$$

IMA BASED UWB RECEIVER DESIGN

In WBAN-related applications, a direct frequency conversion frontend is generally used in the receiver design. This architecture is quite simple, which generally can be used in low power applications. As

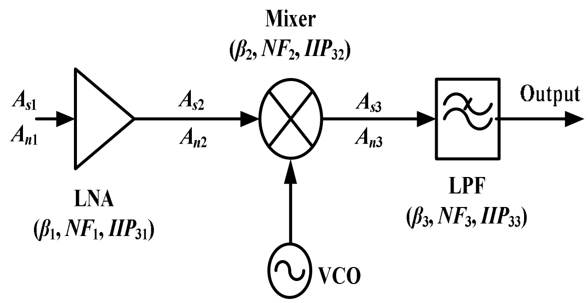

Fig. 2: Direct frequency conversion receiver frontend

shown in Fig. 2, the frontend consists of only three cascading stages: a LNA, a mixer and a LPF. These stages limit the frontend performance in terms of the receiver sensitivity. In order to properly model the receiver frontend, three key parameters of each stage, the small signal gain (β), the Noise Factor (*NF*) and the input referred 3rd order inter-modulation product (IIP_3), are considered. Index i = 1, 2, 3 are used for the LNA, the mixer and the LPF, respectively. The IMA-required objective function is derived from the 9 variables, β_1, β_2, β_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32} and IIP_{33}.

The sensitivity of the UWB receiver is defined as following: the minimum RF input power that results to a pre-determined Bit Error Rate (BER) or SNR at the baseband (for a specified modulation scheme, the BER can be completely determined from the baseband SNR. Therefore, to maximize the baseband SNR for a normalized RF input power is the target of the receiver optimization (Li and Armada, 2011).

An objective function relating the optimized SNR_{out} and the aforementioned 9 variables can be described as follows (Razavi, 1998):

$$SNR_{out} = SNR_{in} \times \frac{1}{NF_1 \cdot NF_2 \cdot NF_3} \times \frac{\beta_1 - \frac{3}{4}\frac{\beta_1}{(IIP_{31})^2} \times (A_{n1})^2}{\beta_1 - \frac{3}{4}\frac{\beta_1}{(IIP_{31})^2} \times (A_{s1})^2} \times \frac{\beta_2 - \frac{3}{4}\frac{\beta_2}{(IIP_{32})^2} \times (A_{n2})^2}{\beta_2 - \frac{3}{4}\frac{\beta_2}{(IIP_{32})^2} \times (A_{s2})^2} \times \frac{\beta_3 - \frac{3}{4}\frac{\beta_3}{(IIP_{33})^2} \times (A_{n3})^2}{\beta_3 - \frac{3}{4}\frac{\beta_3}{(IIP_{33})^2} \times (A_{s3})^2} \quad (9)$$

SNR_{in} is the input signal-to-noise ratio;

A_{ni} and A_{si} are input noise amplitude and signal amplitude of the LNA, the mixer and the LPF, respectively.

The A_{s2}, A_{n2}, A_{s3}, A_{n3} can be deduced by given A_{s1} and A_{n1}:

$$A_{s2} = \beta_1 \times A_{s1} - \frac{3}{4}\frac{\beta_1}{(IIP_{31})^2} \times (A_{s1})^3 \quad (10)$$

$$A_{n2} = \beta_1 \times A_{n1} - \frac{3}{4}\frac{\beta_1}{(IIP_{31})^2} \times (A_{n1})^3 \quad (11)$$

Table 1: Valid ranges of the parameters in IMA

Parameter	Range	Parameter	Range
SNR_{in}	-1~1.5 dB	NF_2	5~20 dB
β_1	0~15 dB	NF_3	-15~5 dB
β_2	-15~10 dB	IIP_{31}	-10~3 dBm
β_3	-15~5 dB	IIP_{32}	-10~0 dBm
NF_1	0~15 dB	IIP_{33}	-10~0 dBm

Table 2: Algorithm implementation flow

Steps	Process
Step 1	Program begin, solution space initiation Initial related parameters in Table 1 Initial particle V, position P, and vector Y
Step 2	Iteration k = 1, particle index i, j = 1
Step 3	Update V and P by Eq. 1 and Eq. 2
Step 4	i = i + 1 , if i<Pop_size , to Step 3 ********* Local Search ***********
Step 5	Leader and populace particles division
Step 6	Update V and Y by Eq.3 and Eq. 4
Step 7	Calculate δ by Eq. 5, revise the weights of Approaching, Random, and Dispersal
Step 8	Select corresponding tactics to update the particles by Eq. 6, Eq. 7, Eq. 8. ********************************
Step 9	$K = K + 1$, IF $K < MAX\_INERATION$, TO STEP 2

$$A_{s3} = \beta_2 \times A_{s2} - \frac{3}{4}\frac{\beta_2}{(IIP_{32})^2} \times (A_{s2})^3 \quad (12)$$

$$A_{n3} = \beta_2 \times A_{n2} - \frac{3}{4}\frac{\beta_2}{(IIP_{32})^2} \times (A_{n2})^3 \quad (13)$$

By using Eq. 9 as the objective function in the IMA, the systematic design of the UWB-receiver is then turned to be a multi-parameters optimization problem which target for the maximum SNR_{out}. The target of the IMA is to find the correct value of the vector (β_1, β_2, β_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32}, IIP_{33}) that results to the maximized SNR_{out}. In IMA, the population size (*pop_size*) of the initial particle swarms is set to 50 and the maximum iteration (*max_ineration*) is set to 2×10^5. Limited by the practical requirement, the ranges of β_1, β_2, β_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32} and IIP_{33} used in this study are included in Table 1. The initial values of these 9 parameters are generated randomly within the reported range.

The implementation flow of the algorithm is shown in Table 2. Immediately following the initiation step, the CLPSO algorithm is used for all particles updating in global search. In local search, the particles are first divided into leader particles and populace particles.

EXPERIMENTAL RESULTS AND DISCUSSIONS

To show the efficiency of the proposed algorithm, a comparison between the IMA and other conventional PSO optimization approaches, such as PSO*w* (Shi and Eberhart, 1998) CLPSO, ISPO and AdpISPO, is given first. Using the same objective function, each method optimizes SNR_{out} for 10 times and the corresponding convergence characteristic is shown in Fig. 3.

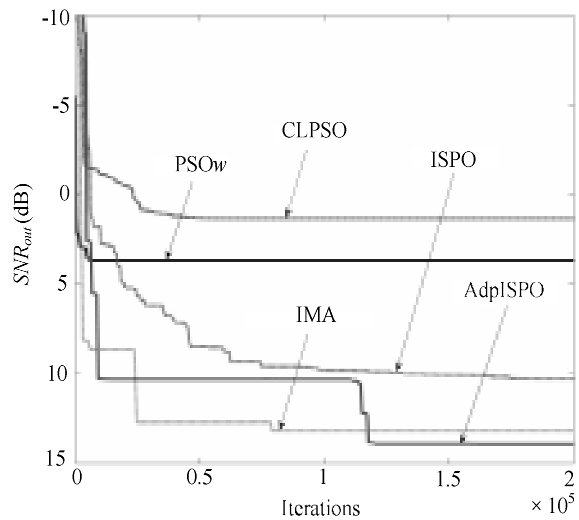

Fig. 3: Convergent curves of each algorithm

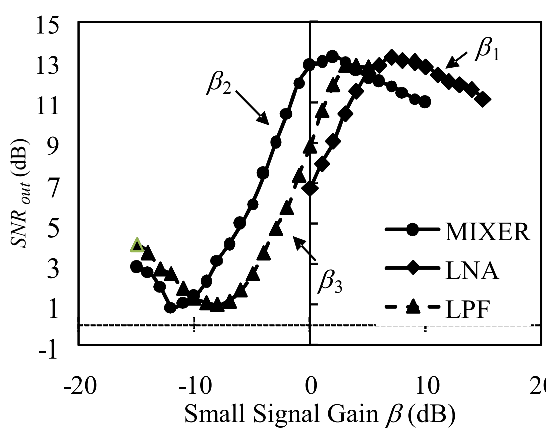

Fig. 4: Relational curves of SNR_{out} and β

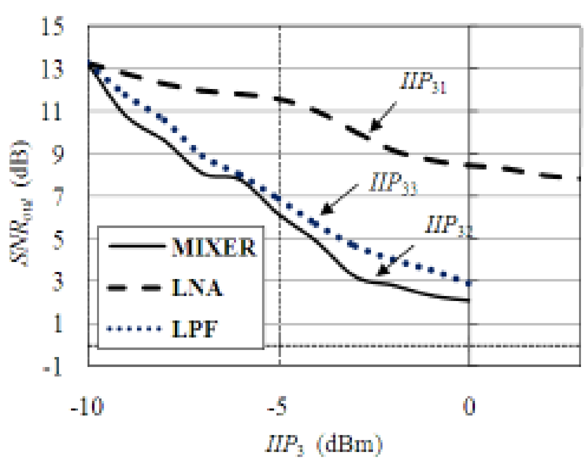

Fig. 5: Relational curves of SNR_{out} and IIP_3

According to the simulation results, the PSO*w*, the CLPSO and the ISPO are not able to converge to the best fitness value in the specific iterations. The AdpISPO can obtain a larger SNR_{out} than the IMA, but with more iterations and time. By introducing a specific local search in the global search, the IMA accelerates the convergence effectively and obtains good performance in less iteration. As shown in Table 3, the SNR_{out} converges to 12.97 dB when the iteration is 8892. Meanwhile, the optimum results of the 9 parameters: β_1, β_2, β_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32} and IIP_{33} are given in Table 4.

Table 3: Optimized results of each algorithm for SNR_{out}

	Algorithms				
Index	PSO*w*	CLPSO	ISPO	AdpISPO	IMA
Iteration	2100	7153	--	15318	8892
SNR_{out}	3.43	2.13	9.75	13.82	12.97

Table 4: The optimized parameter results obtained in IMA

Parameter	Range	Parameter	Range
SNR_{out}	12.97 dB	NF_2	5.6327 dB
β_1	6.8542 dB	NF_3	1.1523 dB
β_2	2.1452 dB	IIP_{31}	-9.8458 dBm
β_3	3.2354 dB	IIP_{32}	-9.9984 dBm
NF_1	0.9852 dB	IIP_{33}	-9.8269 dBm

Table 5: The parameters setting and SNR_{out} obtained in ADS

Parameter	Range	Parameter	Range
SNR_{out}	12.63 dB	NF_2	5.60 dB
β_1	6.90 dB	NF_3	1.20 dB
β_2	2.10 dB	IIP_{31}	-10 dBm
β_3	3.20 dB	IIP_{32}	-10 dBm
NF_1	1.00 dB	IIP_{33}	-10 dBm

In order to measure the validity of these parameters obtained by the IMA, an ADS simulation is used. Considering the practical limits and the discreteness of the receiver component, a group of practical parameters in Table 5 are chosen to simulate in ADS.

The SNR_{out} in ADS is 0.34 dB smaller than the result in IMA. The main reason is the error between the discrete practical parameter values and the continuous results in MA, but the difference is slight. Therefore, the SNR_{out} in MA is very close to the SNR_{out} in ADS in different accuracy.

In order to verify the results found by the IMA, the relationship between the 9 parameters and the SNR_{out} is also studied in ADS. The relational curves described the SNR_{out} and the small signal gain β in each stage are given in Fig. 4. The small signal gain varied step by step in its range (Table 1) and other parameters remained stable. For the LNA, the mixer and the LPF, the results were obtained by varying their small signal gains (β_1, β_2 and β_3), respectively. It is noted that the SNR_{out} is maximal at $\beta_1 = 7.0$, $\beta_2 = 2.0$ and $\beta_3 = 3.0$. Therefore, it can be proved that the values of β_1, β_2 and β_3 found by the IMA metod are the optimum points.

The noise factor *NF* and the 3rd order inter-modulation product IIP_3 were studied in the same way. Experiment results show that the SNR_{out} stays largely constant when the noise factor *NF* varied in valid range. For the IIP_3, it can be found that the SNR_{out} decreased in a mononous maner while the IIP_3 varied around the best performance point (around -10 dBm), as shown in Fig. 5. Therefore, the parameters found by the IMA are optimum results in their valid ranges.

CONCLUSION

This study presents a systematic design and optimization method for the UWB receivers used in WBAN applications. This method uses the IMA to calculate the required small signal gain, the noise factor and the 3rd inter-modulation products of the main receiver blocks that results the optimized baseband SNR. Combining the CLPSO and AdpISPO algorithm to the Memetic framework, the IMA shows faster convergence speed and therefore is more efficient compared to other traditional multi-parameter optimization algorithms. The UWB receiver with the calculated parameter values is validated through ADS simulations.

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