

## Optimization of UWB Receiver using the Improved Memetic Algorithm in WBAN

Qi-Ming Zeng, Hang Yu, Yan Li, Lai Jiang and Zhen Ji

College of Computer Science and Software Engineering, Shenzhen

University, Shenzhen City Key Laboratory of Embedded System Design, Shenzhen, China

**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

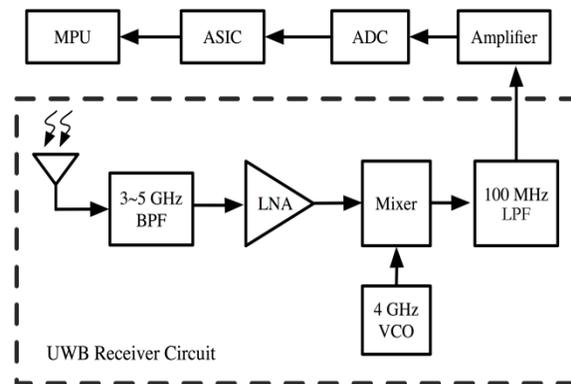


Fig. 1: Block diagram of the UWB receiver circuit

(MA), could be utilized. MA is a hybrid biological heuristic optimization method framework (Moscatto, 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).

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 (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  $k^{\text{th}}$  dimension of the  $i^{\text{th}}$  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  $i^{\text{th}}$  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:

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

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

$V$  = 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  $j^{\text{th}}$  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  $\delta$  is defined as follow:

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

$\text{fitness}()$  is the fitness function;

$\text{lastvalue}$  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:

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

$[P_{\min}, P_{\max}]$  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

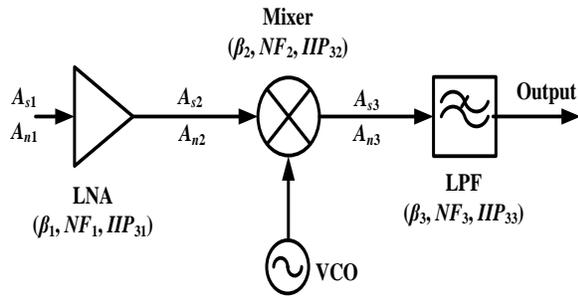


Fig. 2: Direct frequency conversion receiver frontend

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 ( $\beta$ ), the Noise Factor ( $NF$ ) and the input referred 3<sup>rd</sup> 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,  $\beta_1, \beta_2, \beta_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32}$  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):

$$SNR_{out} = SNR_{in} \times \frac{1}{NF_1 \cdot NF_2 \cdot NF_3} \times \frac{\beta_1 - \frac{3}{4} \frac{\beta_1}{(IIP_{31})^2} \times (A_{n1})^2}{\beta_1 - \frac{3}{4} \frac{\beta_1}{(IIP_{31})^2} \times (A_{s1})^2} \quad (9)$$

$$\times \frac{\beta_2 - \frac{3}{4} \frac{\beta_2}{(IIP_{32})^2} \times (A_{n2})^2}{\beta_2 - \frac{3}{4} \frac{\beta_2}{(IIP_{32})^2} \times (A_{s2})^2} \times \frac{\beta_3 - \frac{3}{4} \frac{\beta_3}{(IIP_{33})^2} \times (A_{n3})^2}{\beta_3 - \frac{3}{4} \frac{\beta_3}{(IIP_{33})^2} \times (A_{s3})^2}$$

$SNR_{in}$  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
$\beta_1$	0~15 dB	$NF_3$	-15~5 dB
$\beta_2$	-15~10 dB	$IIP_{31}$	-10~3 dBm
$\beta_3$	-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 $\delta$ 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_ITERATION, TO STEP 2

$$A\beta A = 2 \times s_2 - \frac{3}{4} \frac{\beta_2}{(IIP_{32})^2} \times (s_2)^3 \quad (12)$$

$$A\beta A = 2 \times n_2 - \frac{3}{4} \frac{\beta_2}{(IIP_{32})^2} \times (n_2)^3 \quad (13)$$

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  $(\beta_1, \beta_2, \beta_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32}, IIP_{33})$  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 ( $max\_iteration$ ) is set to  $2 \times 10^5$ . Limited by the practical requirement, the ranges of  $\beta_1, \beta_2, \beta_3, NF_1, NF_2, NF_3, IIP_{31}, IIP_{32}$  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 PSOW (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.

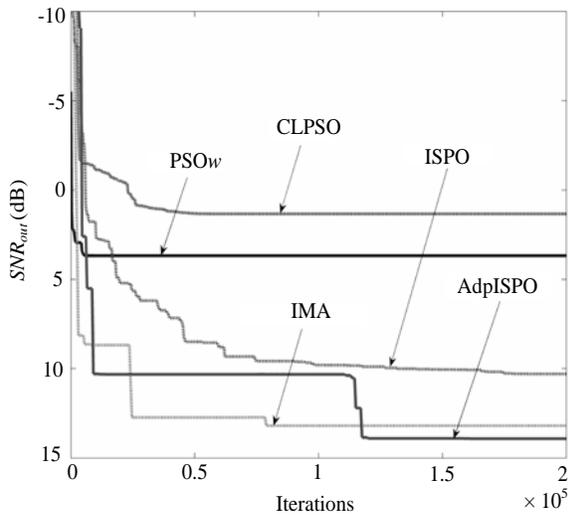


Fig. 3: Convergent curves of each algorithm

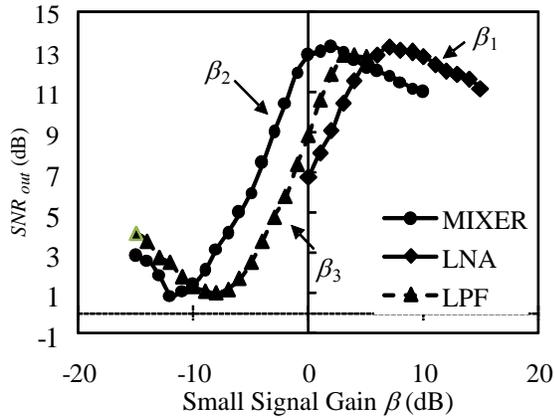


Fig. 4: Relational curves of  $SNR_{out}$  and  $\beta$

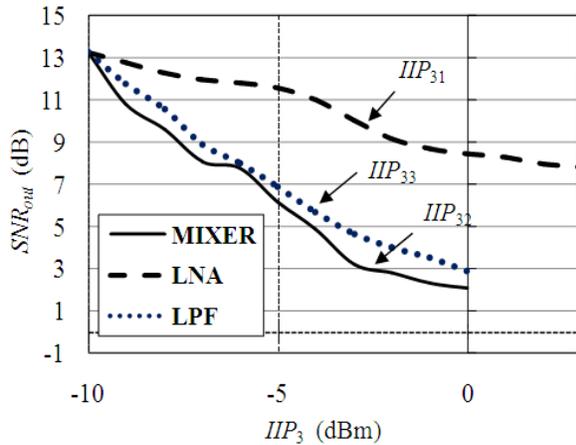


Fig. 5: Relational curves of  $SNR_{out}$  and  $IIP_3$

According to the simulation results, the PSOw, the CLPSO and the ISPO are not able to converge to the best fitness value in the specific iterations. The

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

Index	Algorithms				
	PSOw	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
$\beta_1$	6.8542 dB	$NF_3$	1.1523 dB
$\beta_2$	2.1452 dB	$IIP_{31}$	-9.8458 dBm
$\beta_3$	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
$\beta_1$	6.90 dB	$NF_3$	1.20 dB
$\beta_2$	2.10 dB	$IIP_{31}$	-10 dBm
$\beta_3$	3.20 dB	$IIP_{32}$	-10 dBm
$NF_1$	1.00 dB	$IIP_{33}$	-10 dBm

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:  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ ,  $NF_1$ ,  $NF_2$ ,  $NF_3$ ,  $IIP_{31}$ ,  $IIP_{32}$  and  $IIP_{33}$  are given in Table 4.

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  $\beta$  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 ( $\beta_1$ ,  $\beta_2$  and  $\beta_3$ ), 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  $\beta_1$ ,  $\beta_2$  and  $\beta_3$  found by the IMA method are the optimum points.

The noise factor  $NF$  and the 3<sup>rd</sup> order intermodulation 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 monotonous manner 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.

## ACKNOWLEDGMENT

The authors would like to thank the National Natural Science Foundation of China (NSFC) under grant No. 60901016 and 61201042. The work is also partly supported by the project S2012010010255 and S2011040001460 of Guangdong R/D Foundation under grant and the project JC201005280477A, 2011006 and JCYJ20120613114541904 of Shenzhen city.

## REFERENCES

- Bogale, T.E., L. Vandendorpe and B.K. Chalise, 2012. Robust transceiver optimization for downlink coordinated base station systems distributed algorithm. *IEEE T. Signal Proc.*, 60(1): 337-350.
- Henrik, S., B. Anderson and B. Carl, 2005. A receiver architecture for devices in wireless body area networks. *IEEE J. Emerg. Select. Top. Circ. Syst.*, 2(1): 82-95.
- Ji, Z., J.R. Zhou, H.L. Liao and Q.H. Wu, 2010. A novel intelligent single particle optimizer. *Chinese J. Comp.*, 33(3): 556-561.
- Jiang, M. and L. Hanzo, 2010. Unitary linear dispersion code design and optimization for MIMO communication systems. *IEEE Signal Proc. Lett.*, 17(5): 497-500.
- Keong, H.C., M.R. Yuce and T. M. Chiam, 2010. On-body evaluation of UWB receiver position for wireless body area network. *Proceeding of IEEE International Conference on Ultra-Wideband*.
- Li, H. and A.G. Armada, 2011. Bit error rate performance of MIMO MMSE receivers in correlated rayleigh flat-fading channels. *IEEE T. Vehic. Technol.*, 60(1): 313-317.
- Liang, J.J., A.K. Qin, P.N. Suganthan and S. Baskar, 2006. Comprehensive learning particle swarm optimizer for global optimization of multimodal functions. *IEEE T. Comp.*, 10(3): 281-295.
- Moscato, P., 1999. Memetic Algorithm: A Short Introduction, In: *New Ideas in Optimization*. McGraw-Hill, London, pp: 219-234.
- Razavi, B., 1998. *RF Microelectronics*. Prentice Hall, Upper Saddle River, NJ, pp: 335, ISBN: 0138875715.
- Roslee, M. and K.S. Subari, 2010. Simulation of frequency modulated continuous wave ground penetrating radar using Advanced Design System (ADS). *Proceeding of IEEE Asia-Pacific Conference on Applied Electromagnetics*.
- Shi, Y. and R.C. Eberhart, 1998. A modified particle swarm optimizer. *Proceeding of International Conference on Evolutionary Computation*, Piscataway, pp: 69-73.
- Wong, A.W., D. McDonagh and G. Kathiresan, 2008. A 1 V micropower system-on-chip for vital-sign monitoring in wireless body sensor networks. *Proceeding of Digest of Technical Papers. IEEE International Solid-State Circuits Conference (ISSCC)*, Toumaz Technol., Abingdon, Abingdon, pp: 138-139.
- Yuce, M.R., K. Ho Chee and C. Moo Sung, 2009a. Wideband communication for implantable and wearable systems. *IEEE Microw. Theory Techniq.*, 57(1): 2597-2604.
- Yuce, M.R., T. Dissanayake and H.C. Keong, 2009b. Wireless telemetry for electronic pill technology. *IEEE Sensors, Sch. of Electr. Eng. and Comput. Sci., Univ. of Newcastle, Callaghan, NSW, Australia*, pp: 1433-1437.
- Zhou, J.R., W.G. Huang, T. Tian and Z. Ji, 2010. Face recognition using gabor wavelet and self-adaptive intelligent single particle optimizer. *Chinese Conference on Pattern Recognition, Chongqing, China*.