A PSO-based UWB Pulse Waveform Design Method

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***Abstract*— Based on linear combination with differential Gaussian pulse, a designing impulse radio waveforms method for Ultra Wideband (UWB) wireless communications was investigated. According to the spread spectrum effect of the shaping factor and differential coefficient, a simple pulse design method on constructing differential Gaussian pulse was proposed that made use of a linear only triple-pulse combination of multiple Gaussian derivatives. To gain the best weight coefficient, we proposed to optimize its weight vector and shaping factor by particle swarm optimization (PSO) technique, which is an optimization method inspired by swarm behavior. In PSO algorithm, each particle (individual) belonging to the swarm searches optimal solution efficiently using entire swarm information. The simulation results showed that the designed pulse can meet the power spectral constraint of Federal Communication Commission (FCC) UWB mask. Furthermore, its performance is better than single Gaussian derivation pulse to satisfy some demand.**

Keywords- Gaussian derivative; PSO algorithm; UWB pulse; spectral shaping

I. INTRODUCTION

UWB radio is a promising technology for high data rate short-distance wireless communication. UWB systems have low power consumption, reduced complexity, immunity to multipath fading and high frequency band utilization compared to the narrowband (NB) communication systems. UWB systems take up large bandwidth due to making use of extremely short duration pulses. FCC defined that UWB signal is a signal that has comparative bandwidth is no less than 20% or occupies bandwidth greater than 500MHz of the spectrum [1]. UWB systems operate within frequency range of 3.1-10.6 GHZ. In order to reduce interference with existent NB and make good use of spectrum, FCC has regulated spectrum mask for UWB indoor and outdoor systems allowing a maximum transmitted spectral density of -41.3dBm/MHZ. Many researches have been done for designs of UWB pulses. The standard Gaussian mono-pulse [2] can not meet the FCC spectral mask requirements. A digital UWB pulse generation algorithm based on eigenvalue decomposition was proposed [3].

Using Rayleigh's pulses to design UWB pulse was presented [4]. Design of the family of orthogonal and spectrally efficient UWB waveforms was proposed [5], [6]. Here we research pulse design method based on Gaussian derivatives that were produced considerably easily and used broadly, proposed a simple pulse design method making use of a linear multi-pulse combination of a Gaussian derivation and through analyzing the effect of the shape factor α_i and the weight factor w_i of linear combination on spectrum distribution we proposed to optimize its weight vector and shaping factor by PSO algorithm and we will do experiments to prove this method efficient.

II. GAUSSIAN DERIVATIVE

The basic Gaussian pulse in time domain is shown as

$$f(t)=-\frac{\sqrt{2}}{\alpha}\exp\left(\frac{-2\pi t^2}{\alpha^2}\right) \tag{1}$$

where $\alpha^2=4\pi\sigma^2$ is pulse shaping factor, σ^2 is variance. The differential form of $p(t)$ is $f^{(k)}(t)$, its frequency domain expression through the Fourier transform is shown as

$$F_k(f)=\sqrt{\alpha}\left(2\pi f\right)^k \exp\left(-\pi f^2\alpha^2/2\right) \tag{2}$$

The power spectral density (PSD) is expressed as

$$P_k(f)=\left|F_k(f)\right|^2=\alpha\left(2\pi f\right)^{2k}\exp\left(-\pi^2 f^4\alpha^4/4\right) \tag{3}$$

A. Pulse Shaping Factor

When pulse shaping factor α changed, Gaussian pulse duration will change. Generated waveforms of Gaussian Pulse in the time domain and frequency domain were

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illustrated in Fig. 1 and Fig. 2 with α changing. From Fig. 1 and Fig. 2 we knew the pulse width decreased with α increasing.

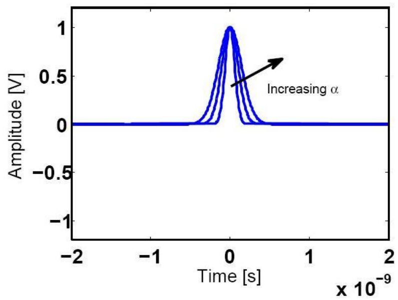

Fig. 1: The Gaussian pulse changed with α (Time domain)

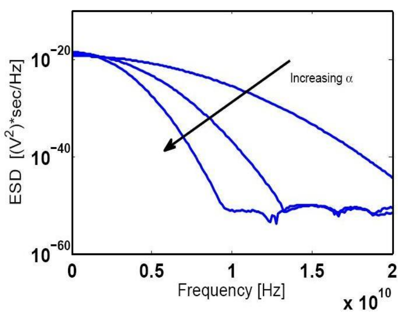

Fig. 2: The Gaussian pulse changed with α (Frequency domain)

B. Derivative Order

If α is constant and k increases then the spectrum energy will distribute in the high frequency band. To explain the influence, the frequency domain waveform of Gaussian derivatives were illustrated in Fig. 3. Where α equaled to 0.625ns. We can see the PSD removed to higher frequency with the order augment of Gaussian derivative order.

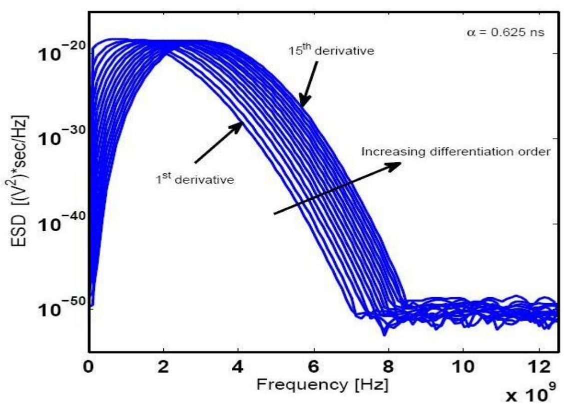

Fig. 3: The Gaussian pulse changing with the increasing derivative order (frequency domain)

III. PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization (PSO) [7], [8] is an optimization method inspired by swarm behavior like a bird flocking. In PSO algorithm, the particles (individuals) have the information of their position and an evaluation value based on an evaluation function. Each individual's moving direction is determined by its present moving direction, its best position in past, and the best position of entire swarm. Then the individual moves with searching the best position that can obtain the best evaluation value. In this section, we describe the basic algorithm of PSO. First of all, we define the number of individuals as N and the dimension of the search space of an optimization as *d*. The position of an individual at k^{th} generation (iteration) is denoted by $X_k[i] \in R^d$, i.q. its velocity and evaluation value are denoted by $V_k[i] \in R^d$ and $J_k[i] \in R$ respectively. The index i= 1,2, ... ,N is the number of the individual. An individual's best position and its evaluation value in past are denoted by $p_k[i] \in R^d$ and $J_{pk}[i] \in R$. The best position and evaluation value of whole swarm including past generation are denoted by $g_k \in R^d$ and $J_{gk} \in R$. You can see the behavior of an individual in 2-dimensional search space in Fig. 4. The basic algorithm is described as follows:

[PSO algorithm steps]

[step 1]

Generate the individuals $X_0[i], \forall i \in [1,2,...,N]$ of initial generation (k=0) randomly.

[step 2]

Compute the evaluation value and update $p_k[i]$ for all individuals.

$$p_k[i]=X_k[i], \text{ if } J_k[i]>J_{pk}[i], \ \forall i . \tag{4}$$

[step 3]

Update g_k by the following equation.

$$g_k[i]=X_k[i], \text{ if } J_k[i]>J_{gk}[i], \ \forall i . \tag{5}$$

[step 4]

Generation change with the following equation.

$$X_{k+1}[i]=X_k[i]+V_k[i], \ \forall i$$

$$V_k[i]=\kappa\times\{V_{k-1}[i]+c_1\times\Gamma(g_k-X_k[i]) +c_2\times\Lambda(p_k[i]-X_k[i])\}, \ \forall i , \tag{6}$$

where, $c_1,c_2,\kappa \in R$ and $\Gamma,\Lambda \in R^{d\times d}$ are denoted by

$$\Gamma=\mathrm{diag}[\gamma_1,\gamma_2,...,\gamma_d]$$

$$\Lambda=\mathrm{diag}[\lambda_1,\lambda_2,...,\lambda_d] \tag{7}$$

where, $\gamma_i \in [0,1]$, $\lambda_i \in [0,1]$ (i=1,2,...,d) are uniform pseudorandom numbers.

[step 5]

k=k+1, then repeat [step 2] through [step 5].

A. Constriction Factor Approach (CFA)

In the PSO algorithm, designing of the value of parameters are very important because it is related to the performance of solution search. For example, in the case of the swarm having a divergent behavior, the individuals are widely distributed in the search area. As a result, PSO algorithm is brought out the performance only similar to a random search. On the other hand, converged swarm searches just a local area and the search efficiency deteriorate significantly in each case. Consequently, there are two leading design methods called IWA (Inertia Weight Approach) [7] and CFA (constriction Factor Approach) [7], [8]. Here we employ typically prevailing CFA design. According to CFA design method, the weighting coefficients c_1, c_2 and κ in equation (3) are decided by following formula.

$$\kappa = \frac{2}{\left|2-\phi-\sqrt{\phi^2-4\phi}\right|} \tag{8}$$

where $\phi = c_1 + c_2$ and $\phi > 4$.

c_1 and c_2 are decided for the total to become 4 or more. Swarm's behavior is gradually converged because any ϕ satisfy $\kappa<1$. therefore, in CFA design method, the weight coefficients which related to X_k, p_k, and g_k respectively are adjusted by only one parameter.

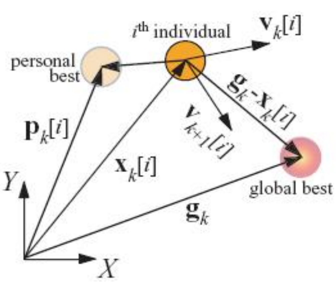

Fig. 4: Behavior of an individual in 2-dimensional search space.

IV. Gaussian Mixture UWB Pulse Design

In this paper, we will analyze the possibility of tuning the PSD of a generated pulse by combining a few single reference Gaussian pulse waveform and its derivatives to adjust the PSD to the mask. A possible approach is to use linear combinations of N Gaussian derivatives, each being characterized by a given α value and combined them linearly with different weight factors into a pulse. Note that the combination of N derivatives and the possibility of choosing different α values for different derivatives provide a high degree of flexibility in the generation of pulse waveforms. The combinational pulse was:

$$p(t)=\sum_{i=1}^{N} a_i f^{(i)}(t,\alpha_i) \tag{9}$$

where a_i was weight factor, α_i was pulse shaping factor. We want to design and compare combinational UWB pulses from two aspects: random combination, and error minimization such as the Least Square Error (LSE) or the area between standard UWB emission mask and the PSD of the linear combination signal via PSO algorithm.

A. Random Combination

Now, we will analyze the problem of emission mask with combination of Gaussian derivatives and perform the approximation through two cases: in the first case, all derivatives have the same shape factor α, while in second case, different derivatives adopt different α values. We generate in a random way a set of coefficients for the first 15 derivatives and check if the PSD of the linear combination of the functions obtained with these coefficients satisfies the emission limits. So as to gain better weight coefficients, we repeated choosing another sets of coefficients until the distance between the mask and PSD of the generated waveform falls below a fixed threshold. Fig. 5 and Fig. 6 show the PSD of the waveforms obtained by random combination of the first 15 derivatives plotted against the FCC emission mask based on the weight coefficient and shape factors of the combined UWB pulses for case 1 and case 2 in table I.

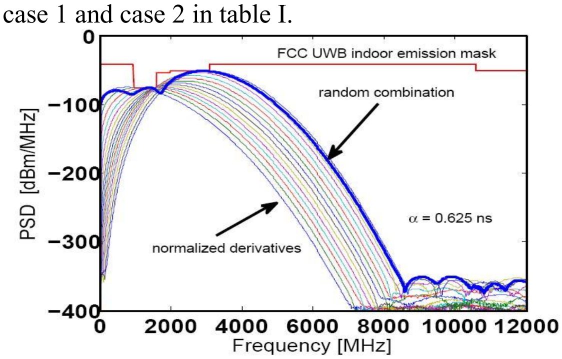

Fig. 5: Random combination (case 1)

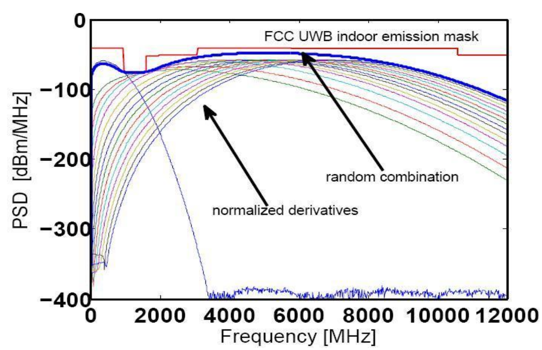

Fig. 6: Random combination (case 2)

Fig. 5 shows that the combination of several Gaussian derivatives leads to a good approximation of the emission mask, in particular in the band 0.96 GHz- 3.6 GHz. Outside this band, power is less efficient used. But the spectral performance of case 2 is better than case 1 and single Gaussian derivation pulse.

B. UWB Pulse Design Using PSO Algorithm

Random selection is only one of the possible strategies for the set of coefficients in the linear combination. In fact if the weight vector of linear combination was selected randomly, the attained combination pulse may be not best and most appropriate, so proposed to optimize the weight vector using PSO. In PSO algorithm the evaluation function definition was very important. The goal to optimizing weight vector was to make combination pulse be close to FCC emission mask to the greatest extent, in other words to make error between them minimum. So we defined two evaluation functions as below:

a) Least square error (LSE) evaluation function: a more systematic way of selecting such coefficients is to apply our procedure for error minimization such as the least square error (LSE), in which the following error function must be minimized:

$$e_{s1}(t)=\int_{-\infty}^{+\infty}\left|e_1(t)\right|^2dt=\int_{-\infty}^{+\infty}\left|f(t)-\sum_{k=1}^{N}a_kf_k(t)\right|^2dt \qquad (10)$$

In equation (10), f(t) is the target function. Note that since requirements are specified in terms of meeting a PSD, the error equation (10) rewrites as follows:

$$e_1=\int_{-\infty}^{+\infty}\left|P_M(f)-F(f)\right|^2df \qquad (11)$$

where $P_M(f)$ was FCC emission mask, F(f) was PSD of linear combination pulse.

b) The area, between standard UWB emission mask and the PSD of the linear combination error function: we define error function as below formula

$$e_2=\left|\int_{0}^{10.6}\left(P_M(f)-F(f)\right)df\right| \qquad (12)$$

e_2 is the area between FCC emission mask and the Gaussian derivatives. e_1 and e_2 are error functions and we hoped to find the weight vector that made e_1 and e_2 get to its minimum.

TABLE I. THE WEIGHT COEFFICIENTS AND SHAPE FACTORS OF THE COMBINED UWB PULSES FOR CASE 1 AND CASE 2.

	Case 1		Case 2	
i	α_i	w_i	α_i	w_i
1	0.625 ns	-0.038	1.525 ns	-0.082
2	0.625 ns	0.003	0.325 ns	0.355
3	0.625 ns	-0.013	0.325 ns	0.076
4	0.625 ns	0.045	0.325 ns	0.831
5	0.625 ns	-0.044	0.325 ns	-0.860
6	0.625 ns	0.091	0.325 ns	-0.973
7	0.625 ns	-0.029	0.325 ns	0.903
8	0.625 ns	0.236	0.325 ns	0.030
9	0.625 ns	0.505	0.325 ns	0.500
10	0.625 ns	0.062	0.325 ns	0.217
11	0.625 ns	0.615	0.325 ns	0.697
12	0.625 ns	-0.778	0.325 ns	0.494
13	0.625 ns	0.078	0.325 ns	-0.144
14	0.625 ns	-0.550	0.325 ns	0.181
15	0.625 ns	0.817	0.325 ns	0.790

C. Coding Rules

In PSO, individuals of the k^{th} generation have information of position $X_k[i]$, velocity $V_k[i]$ and its evaluation value $J_k[i]$. In addition, these individuals remember a past best position $p_k[i]$ of itself. PSO is an optimization technique by the generational change to search for the position which the high evaluation value. The generational change is implemented based on $X_k[i]$, $V_k[i]$, $p_k[i]$, and past best position of the swarm g_k. Here we would use PSO to optimize the vector $\left[\alpha_j \quad w_j\right]$ of linear combination of Gaussian derivatives. We denoted this vector by $X_k^{d_m}[i]$, where i (i=1,2,...,N) was the i^{th} particle at k^{th} generation, m was the length of each particle or the dimension of the search space of PSO algorithm. Combination pulses are composed of the 15 single pulses, so the length of vector was 30. When optimizing problems, PSO involved parameters such as population size N that was the number of individuals in population, dimension of the search space of an optimization as d, and the maximum iteration S. Here N was supposed to be 10, chose maximum iteration to be 20 and d equaled to 30.

At the first step we generated the initial population randomly, and then in the following, STEP 2, 3, 4 and 5 are applied to all individuals. For example for i=1, we have

$$\begin{array}{ll} X_0^{d_m}[1]=\left[X_0^{d_1}[1] \ \cdots \ X_0^{d_{30}}[1]\right] & 1^{th}\text{ particle at }1^{th}\text{ generation} \\ \vdots \qquad \vdots \qquad \vdots & \vdots \\ X_0^{d_m}[10]=\left[X_0^{d_1}[10] \ \cdots \ X_0^{d_{30}}[10]\right] & 10^{th}\text{ particle at }1^{th}\text{ generation} \end{array} \qquad (13)$$

[step 2]

Compute the evaluation value according to the relation (11) or (12) for minimizing error function and update $p_k[i]$ for all individuals based on (4).

[step 3]

Update g_k by formula (5).

[step 4]

Update Generation of the swarm from k to k+1 by equation (6) and then repeat [step 2] through [step 4].

[step 5]

Re-initialization of the swarm by following formulation return to Gaussian derivatives.

$$X_k[i]=g_k-\delta\left(R_{max}-R_{min}\right)\times(2\gamma-1) \qquad (14)$$

Individuals which went out of the search area are returned to following position

$$\begin{array}{lll} X_k[i]=R_{max}-2\delta\cdot\gamma\left(R_{max}-R_{min}\right) & \text{if} & X_k[i]>R_{max} \\ X_k[i]=R_{min}+2\delta\cdot\gamma\left(R_{max}-R_{min}\right) & \text{if} & X_k[i]<R_{min} \end{array} \qquad (15)$$

Where R_{min} and R_{max} are minimum and maximum value of the search area respectively, δ is range of a controllable power factor, and $\gamma\in[0,1]$ denotes a uniform pseudorandom number.

V. SIMULATION RESULTS

In Fig. 7 and Fig. 8 PSO optimized the vector $\left[\alpha_j \quad w_j\right]$ of Gaussian derivatives linear combination. For k=1, 4, 5 when we used equations (11) and (12), we obtained the best value of vector $[\alpha_1 \ \ \alpha_4 \ \ \alpha_5 \ \ w_1 \ \ w_4 \ \ w_5]$ based on the

Gaussian derivatives linear combination via PSO algorithm equaled to $[1.96\text{ ns} \quad 0.0758\text{ ns} \quad 0.231\text{ ns} \quad -0.0079 \quad -0.0323 \quad 0.0391]$ and $[2.044\text{ ns} \quad 0.100\text{ ns} \quad 0.211\text{ ns} \quad -0.0180 \quad -0.0313 \quad 0.2872]$ respectively. From Fig. 7 and Fig. 8 we can know that the optimized pulse by PSO met the FCC emission mask in whole frequency band, it was better than single Gaussian derivative pulse and had much larger PSD than random combination pulse under satisfying condition.

VI. CONCLUSIONS

Single Gaussian pulse usually could not meet FCC emission mask perfectly. This paper combined Gaussian derivatives linearly to implement UWB pulse designed at the same time proposed to optimize pulse shape factor and weight vector using PSO. We adopted first, fourth and fifth order Gaussian derivatives as basis functions, and constructed the PSO model on optimizing pulse shaping and weight vector. The simulation results showed these two combination pulses met FCC emission mask better compared with the random combination pulse or single derivative pulse, which proved the UWB pulse design method based on PSO was best of other methods and successful.

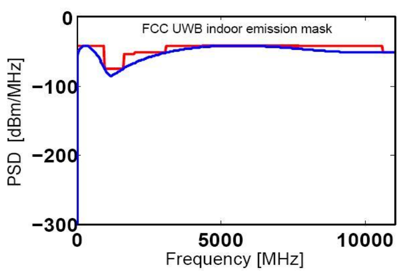

Fig. 7: The PSD of PSO linear combined UWB pulse using e_1

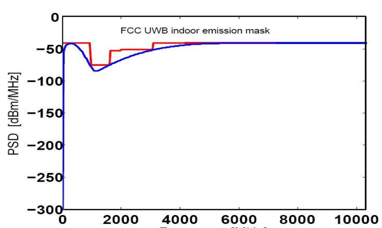

Fig. 8: The PSD of PSO linear combined UWB pulse using e_2

ACKNOWLEDGMENT

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