

Efficient Design of Pulse Compression Codes Using Multiobjective Genetic Algorithm

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Abstract

Binary sequences having good aperiodic autocorrelation functions (ACFs) with low range sidelobes are required for many communication applications. However, few such good binary sequences are available having large sequence length. In this paper nondominated sorting genetic algorithm-II (NSGA-II) is used to generate biphase pulse compression codes from length 49 to 100. Pulse compression technique avoids the transmission of a signal having small pulse width and high peak power for better range resolution. The efficiency of these codes depends upon the energy content in the range sidelobes of their autocorrelation functions. Peak sidelobe level (PSL) and integrated side lobe level (ISL) are the two performance measures for pulse compression codes. In this paper the multi objective problem is designed by taking PSL and ISL as the objective functions.

1. Introduction

In a pulse radar system the transmitted pulse width should be as long as possible to increase the sensitivity of the system and as small as possible at the receiver for better range resolution. Range resolution is the ability of the radar receiver to discriminate nearby targets. The performance of range resolution radar would be optimal, if the coded waveform has impulsive autocorrelation. In pulse compression technique a long coded pulse is transmitted and the received echo is processed to obtain a relatively narrow pulse. Thus increased detection capability of a long pulse radar system is achieved while retaining the range resolution capability of a narrow pulse system. The range resolution is determined by bandwidth of the signal. Wide bandwidth is necessary for good range resolution. The signal bandwidth is obtained by modulating phase or frequency of the signal, while maintaining constant pulse amplitude. Mostly biphase pulse compression is used in radar system in which the phase of the transmitted signal is 0 degree relative to a local reference for a '+1' in the binary code and 180 degree for a'-1'. Phase coding can be used to reduce radio frequency interference between adjacent radar and make the waveform more robust to interference. Phase coded

(PC) waveforms support better range-resolution compared with linear frequency modulated (LFM) pulses because the windowing functions used with LFM pulses to lower time sidelobes cause a broadening in the mainlobe response and a deterioration in range resolution, which is not present with phase coding. But the autocorrelation of phase coded waveforms contain range sidelobes, which have a negative influence on the detection performance of radar. These sidelobe can mask useful information and may give undesired gain to the signal from the unwanted target. A desirable property of the compressed pulse is that it should have low sidelobes in order to prevent a weak target from being masked in the time sidelobes of a nearby stronger target. The lower the sidelobes, relative to the main lobe peak, the better the main peak can be distinguished and, therefore the better is the corresponding code. The compressed pulse should not significantly degraded when the return signal has been doppler shifted due to target motion. Most of the modern radars incorporate pulse compression waveforms to avoid transmission of a pulse having a large peak power. The selection of a pulse compression codes depends upon the application and the environmental conditions. If the application is radar designed for a scenario dominated by distributed clutter then integrated side lobe level (ISL) is very important. On the other hand if the application requires detection of targets in the presence of large discrete clutter then the peak side lobe level (PSL) is more important. If the desired ISL or PSL performance is not achieved with a matched filter, some signal to noise ratio (SNR) gain may be sacrificed and a mismatch filter may be used to achieve the desired side lobe level.

Sequences having low off-peak signal value at the output of the matched filter have found extensive applications in radar and communication systems. Binary pulse compression codes such as the Barker code [1] or maximal-length sequences [2] are extensively used in many radar systems. The digital matched filter for the binary code is much less complex than the polyphase code, and the clutter rejection performance of the binary code is fair while that of the chirp method is poor. Barker sequences are the only known binary sequences with the lowest PSL of unity. The longest available barker sequence is of length 13.Many practical applications require longer codes to achieve higher signal to noise ratio. By exhaustive computer search program, Lindner [3] found all binary sequences up to length 40 with minimum PSL. Cohen et al. [4] extended those results to length 48. Using a neural network approach, Hu et al. [5] obtained useful binary sequences for lengths up to 100.Kerdock et al. [6] found the maximum length of a code for a given peak sidelobe level. Boehmer[7] has developed an analytical technique for generating good binary pulse compression codes. Rao and Reddy [8] has obtained larger length binary sequences with minimum sidelobes in their aperiodic autocorrelation pattern by cyclically shifting the Legender sequences.Levanon [9] used mismatch processing to optimize integrated or peak sidelobe levels of long binary signals. Baden and Cohen [10] has explained a method for generating a filter that minimizes the energy in the side lobes after multiplying the sidelobes by a given weighing function. Therefore the pulse compression problem of radar may be viewed as a multiobjective problem in the sense that the PSL and ISL need simultaneous minimization. This burning issue has been studied in [5] using artificial neural network (ANN) technique but not as a multiobjective problem.

The organization of the paper is as follows. In section 2, the basis of generating new aperiodic codes is outlined as a multiobjective optimization problem in which the PSL and ISL are simultaneously optimized. The multiobjective tool used as to optimize these two objective functions is discussed in section 3. The new sequences generated by the proposed method are obtained by NSGA-II through simulation study using MATLAB and are listed in section 4. Finally in section 5 the conclusion of the investigation is highlighted.

2. Multiobjective Formulation

Let an L length binary sequence is given by

$$S = \{s_1, s_2, s_3, \cdots, s_L\}$$
(1)

where each element of S has value is either +1 or -1.

The output of the matched filter that is the aperiodic autocorrelation function for positive delays is given as

$$C_k(S) = \sum_{i=1}^{L-k} s_i s_{i+k}$$
(2)

where $k = 0, 1, 2, \dots, L - 1$

A significant problem inherent in biphase pulse compression is that the autocorrelation function does not yield a perfect impulse, that means it does not produce $C_k(S) = 0$ for $k \neq 0$. Any non zero value of $C_k(S)$ for $k \neq 0$ is referred to as sidelobe where as the zero-offset correlation value $C_0(S)$ is called the mainlobe. The difference between a pulse compression waveform and a simple pulse waveform is in the existence and magnitude of these sidelobes. The amplitude of the main peak of an autocorrelation is a measure of signal-to-noise ratio improvement for a given code. The sidelobes limit the usefulness of a code regardless of the strength of the mainlobe. This is because sidelobes signify "self noise" which may be much greater than the system noise. Codes are chosen for a given application based on their length and sidelobe levels.

There are two frequently used sidelobe measures. The first one is the peak sidelobe level(PSL) which is the largest sidelobe in the autocorrelation function of the code and is defined as

$$PSL = Max \left| (C_k(S)) \right|, k \neq 0 \tag{3}$$

The second is the integrated sidelobe level (ISL) defined as the total energy contained in all the sidelobes. As the signal is real valued the autocorrelation is real and symmetric about the zero delay. The ISL is represented as

$$TSL = 2\sum_{k=1}^{L-1} C_k^2(S)$$
 (4)

The PSL and ISL is represented as the terms defined in (3) and (4) are simultaneously minimized to achieve desired aperiodic codes.

3. Nondominated Sorting Genetic Algorithm-II

In 1967, Rosenberg suggested a genetic search to the simulation of genetics and the chemistry of a population of single-celled organisms with multiple properties or objectives [11]. Genetic algorithm (GA) was originally proposed by J. Holland [12] which imitates Nature's robust way of evolving successful organisms. The first practical algorithm, called vector evaluated genetic algorithm (VEGA), developed by Schaffer [13]. One of the constraints of VEGA is its bias towards some Pareto-optimal solutions. Subsequently Deb and Srinivas [14] proposed the nondominated sorting genetic algorithm(NSGA) which is a popular nondomination based genetic algorithm for multi-objective optimization problem. It is a very effective algorithm but has been generally not preferred for its heavy computational complexity, lack of elitism and for choosing the optimal parameter values. A modified version, NSGA-II was developed by Deb et al. [15] as a better sorting algorithm which incorporates elitism and without using a sharing parameter. A brief outline of NSGA-II algorithm is given below.

- 1) **Population Initialization**: The population contains a set of chromosomes. Each chromosome is initialised randomly with binary bits having length same as the code length.
- 2) **Non-Dominated sort**: The initialized population is sorted based on non-domination
 - for each individual p in main population P perform the following

- Initialize the set of individuals dominated by p $S_p = \phi$.
- Initialize the number of individuals that dominate p i.e. $n_p = 0$.
- for each individual q in P
 - * if p dominates q then
 - $\cdot \ S_p = S_p \cup \{q\}$
 - * else if q dominates p then
 - $\cdot n_p = n_p + 1$
- if $n_p = 0$ then p belongs to the first front and rank of individual p i.e. $p_{rank} = 1$. Update the first front F_1 by adding p to front one i.e. $F_1 = F_1 \cup \{p\}$
- This is carried out for all the individuals in main population *P*.
- Initialize the front counter i = 1
- perform the following if i^{th} front is nonempty i.e. $F_i \neq \phi$
 - $Q = \phi$. The set Q is used to store the members of the next front.
 - for each individual p in front F_i
 - * for each individual q in S_p
 - $\cdot n_q = n_q 1$, decreament the domination count for individual q
 - · if $n_q = 0$, set $q_{rank} = i + 1$. Update q i.e. $Q = Q \cup q$.
 - -i=i+1.
 - set Q is the next front and hence $F_i = Q$.
- 3) Crowding Distance Assignment: Once the non- dominated sorting is complete the crowding distance is assigned. Since the individuals are selected based on rank and crowding distance, all the individuals in the population are assigned a crowding distance value front wise. The crowding distance is calculated as
 - For each front F_i , n is the number of individuals.
 - Initialize the distance for all individuals to be zero i.e. $F_i(d_j) = 0$, where j corresponds to an individual in front F_i .
 - for each objective function m
 - * Sort the individuals in front F_i based on objective function m i.e $I = sort(F_i, m)$.
 - * Assign infinite distance to boundry values for each individual in F_i i.e $I(d_1) = \infty$ and $I(d_n) = \infty$
 - * for k = 2 to (n-1)

$$\cdot I(d_k) = I(d_k) + \frac{I(k+1) \cdot m - I(k-1) \cdot m}{f_m^{max} - f_m^{min}}$$

- where $I(k) \cdot m$ is the value of the m^{th} objective function of k^{th} individual in I
- Selection: The selection is carried out using a crowded-comparison-operator (≺n). The comparison is carried out as below

- a) non-domination rank p_{rank} i.e. individuals in front F_i will have their rank as $p_{rank} = i$.
- b) crowding distance $F_i(d_j)$
- $p \prec_n q$ if
 - $p_{rank} < q_{rank}$
 - or if p and q belong to the same front F_i then $F_i(d_p) > F_i(d_q)$ i.e the crowding distance of p should be more q.

The individuals are selected using a binary tournament selection with crowded comparison operator.

- 5) Genetic Operators: Single point crossover and mutation operations as used in GA[16] are also employed in NSGA-II.
- 6) **Recombination and Selection**: The offspring population is combined with the current generation population and the total population is sorted based on nondomination. The new generation is filled by chromosomes from each front subsequently until the population size exceeds the current population size N. If by adding all the individuals in front F_j the population exceeds N then individuals in front F_j are selected based on their crowding distance sorted in the descending order until the population size is N.

4. Simulation results

The NSGA-II algorithm dealt in section 3 is used to obtain the desired non periodic binary strings yield lowest possible PSL and ISL. PSL and ISL are the two cost functions are minimized using NSGA-II algorithm to generate binary strings varying the lengths from 49 to 100. The PSL and ISL values for each chromosome are determined according to (3) and (4) respectively. The population is sorted based on nondomination. Each individual in first front are given a rank value of 1 and the same in second is assigned a rank value of 2 and so on. Parents are selected from the population by using binary tournament selection based on the rank and crowding distance. An individual is selected if its rank is less than the other or if its crowding distance is greater than the other. The selected population generate offspring using crossover and mutation operators. The crossover and mutation probability used are 0.8 and 0.1 respectively. The total population including the current population and current off springs is sorted again based on non-domination and only the best N individuals are selected. The selection is based on rank and crowding distance on the last front. The population size N is taken as 200 and the number of generations varied from 150 to 200.As the sequence length increases generations increased to get better result. In multi objective algorithms a pareto front contains more than one sequence for each length. The sequences found by the proposed method for length 49-100 which are better than [5] are listed in Table 1. The PSL and ISL values of [5] are also presented in Table 1 for the purpose of comparison.

Table 1: Sequences

| Seq Len | [| 5] | NSC | GA II | Sequence |
|---------|-----|------|-----|-------|----------------------------------------------------------|
| | PSL | ISL | PSL | ISL | |
| 49 | 5 | 688 | 4 | 560 | 00111110001111110110000001001011001110011010 |
| 49 | 5 | 688 | 5 | 472 | 0011111100111111011000000100101100110100101 |
| 50 | 5 | 674 | 5 | 658 | 0001001001110011110010010100011011101010 |
| 51 | 5 | 618 | 5 | 594 | 11000001000000011010011000100010010111100101 |
| 52 | 5 | 708 | 5 | 604 | 0000110011001100001111000000001010001011010 |
| 53 | 5 | 700 | 5 | 604 | 001001011001000110011110111111100101010000 |
| 54 | 5 | 750 | 5 | 702 | 111001110111010110011110001100111110000101 |
| 55 | 5 | 902 | 5 | 830 | 1000111100010001011111001000110101011111 |
| 56 | 6 | 1000 | 5 | 920 | 001110001000110111000110100010000001001 |
| 56 | 6 | 1000 | 6 | 776 | 0011101010001101110001101000100000010111011010 |
| 57 | 6 | 920 | 6 | 784 | 110110010111110101110101110001100010010 |
| 58 | 6 | 1130 | 5 | 890 | 100101000111011100010101111110000111011001110110010000 |
| 58 | 6 | 1130 | 6 | 698 | 100101000111001100101011011000011101001110110010000 |
| 59 | 5 | 1050 | 5 | 994 | 00000100101100001111111110001010110001111 |
| 60 | 6 | 1212 | 6 | 836 | 11000000101010011100000110101101101101001001100110001111 |
| 61 | 6 | 1068 | 6 | 780 | 10101001011100011111000100111111011101110010000 |
| 62 | 6 | 1094 | 6 | 998 | 1000000110110101010101110100000001000001111 |
| 63 | 5 | 934 | 5 | 902 | 1001101011011110000100000001110100000101 |
| 64 | 6 | 1336 | 6 | 1024 | 0111011101010000101001110100100101101111 |
| 65 | 6 | 1328 | 6 | 1160 | 1111100110100101110100010111001100011100111011010 |
| 66 | 6 | 1410 | 6 | 1010 | 0110001100010100010101101101101101101111 |
| 67 | 6 | 1218 | 6 | 1098 | 1111100000111101111111010110001010010100101 |
| 68 | 6 | 1252 | 6 | 1180 | 10111100110001010101110011100000011010000 |
| 69 | 6 | 1500 | 6 | 1236 | 101100100110010010100011101000101100011100101 |
| 70 | 6 | 1454 | 6 | 1422 | 00101100001100011101001101100000101010000 |
| 71 | 7 | 1860 | 7 | 1518 | 110111000101110010101101101001111010101111 |
| 72 | 7 | 1744 | 7 | 1568 | 010001010111111101010010001111001100101111 |
| 73 | 6 | 1504 | 6 | 1312 | 01000101011011100110010100011111000001111 |
| 74 | 7 | 1786 | 7 | 1578 | 0111001011000011000011101000100100101111 |
| 75 | 6 | 1250 | 6 | 1130 | 0101111010101111000110111001110110010101 |
| 76 | 7 | 1972 | 7 | 1580 | 010100001001000010100011100101110110001111 |
| 77 | 6 | 1560 | 6 | 1396 | 1100101100111001011000011000100010001000101 |
| 78 | 9 | 2150 | 7 | 1670 | 1111111100000110100000010100011100011100101 |
| 79 | 7 | 2246 | 6 | 1526 | 11111010011010001010110100101100010000101 |
| 79 | 7 | 2246 | 7 | 1454 | 01011010011010001010110100101110010000101 |
| | | | | | ** |
| 80 | 8 | 2240 | 7 | 1584 | 10000110001001111000001010111100100110011010 |
| 81 | 7 | 1824 | 7 | 1720 | 00110011100100010101010100000011001011010 |
| | | | | 102- | |
| 82 | 7 | 2162 | 7 | 1826 | 0000001111000001111001010000000001101010 |

continued on the next page ...

| Sequences | (continued |) |
|-----------|------------|---|

| Seq Len | [5] | [5] | NSGA-II | NSGA-II | Seq | |
|---------|-----|------|---------|---------|--------------------------------------------------|--|
| | PSL | ISL | PSL | ISL | | |
| 83 | 7 | 2202 | 7 | 1986 | 010000010101001111010100000111100000100011000101 | |
| 84 | 7 | 2636 | 7 | 2372 | 1011000101111101000011101000110000111100101 | |
| 85 | 7 | 2332 | 7 | 1916 | 1111111000001110110101010010010011011111 | |
| 86 | 7 | 2062 | 7 | 1902 | 0111001101110100010001000111100010100000 | |
| 87 | 8 | 2520 | 7 | 2046 | 00100100001100100111111101110001011110000 | |
| 87 | 8 | 2520 | 8 | 1982 | 00100100001100100101111101110001011110000 | |
| 88 | 7 | 2264 | 7 | 2224 | 1011011000010101111100100011001101001010 | |
| 89 | 7 | 2128 | 7 | 2112 | 011110110100000011000111111010100011110010000 | |
| 90 | 8 | 2698 | 8 | 2346 | 0100011000111100101110100100100000101110111010 | |
| 91 | 7 | 2226 | 7 | 2082 | 111000000000110011111111110011101111100100111010 | |
| 92 | 7 | 2004 | 7 | 1844 | 001101100100110101110010010100111000000 | |
| 93 | 9 | 3316 | 7 | 2476 | 01111011110110011001101000000010100110000 | |
| 94 | 8 | 3062 | 8 | 2630 | 1111001000110001110110001011000110100111000101 | |
| 95 | 8 | 3374 | 8 | 2262 | 111010010010101000010111100001011110110 | |
| 96 | 10 | 3520 | 8 | 2416 | 0001000111110000101000011110111101010110011010 | |
| 97 | 9 | 3576 | 8 | 3440 | 110010111010101110010001000010110000010011101111 | |
| 97 | 9 | 3576 | 9 | 2696 | 010010101000101010010101000010110000010011101111 | |
| 98 | 8 | 2930 | 8 | 2594 | 01000000000110001100001110111011001110000 | |
| 99 | 8 | 2794 | 8 | 2386 | 10111100010010010001000000001101100110 | |
| 100 | 8 | 3748 | 8 | 2508 | 001111100001101101110011100110110101111010 | |

5. Conclusion

By using NSGA-II algorithm as given in section 3 a list of sequences of length 49-100 is obtained, as shown in Table 1 which also contains PSL and ISL value of the sequences.0's are used in place of -1's to conserve space. It is observed from the table that the codes having same PSL value have less ISL value compared to [5].Further it observed that at lengths 49,56,58,79,87 and 97 two different codes are found out of which one code optimal with respect to both PSL and ISL. The result reveals that this method performs better than the approach described in [5]. The search for optimum sequence depends on the selection of the initial population of parent sequences. As the sequence length increases the search procedure requires more time for obtaining a good solution. The quality of solution improves with increase in the number of generations.

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