Parameter Estimation and Prediction of the Chirp and Stochastic Pulse Position Modulation Combined Signal

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Abstract**—**Recent work has proposed a certainty trend (CT) elimination technique employed for the auto-regressive/auto-regressive and moving-average (AR/ARMA) model pulse position prediction. In this paper, we investigate the intra pulse parameter estimation and pulse position prediction of the chirp and stochastic pulse position modulation (CSPPM) combined signal. The quick dechirp method is adopted to the initial frequency and chirp rate estimation. To get a stationary data series satisfying the premise condition of the AR/ARMA model prediction, a least square fitting (LSF) scheme to remove the CT term contained in pulse position sequence is presented. Compared with the classic logarithmic difference conversion (LDC) smooth method, AR/ARMA prediction performance via LSF has a significant improvement, about 70% to 96% for AR prediction and 42% to 99% for ARMA prediction.

Index Terms**—**AR/ARMA model, prediction, stochastic pulse position modulation signal, least square fitting (LSF)

I. Introduction

Recently, the complex signal such as the chirp and stochastic pulse position modulation (CSPPM) combined signal is receiving more and more attention [1]-[3]. M. Kaveh and G.R. Cooper introduced the notion of the stochastic pulse position modulation (SPPM) signal in [4] and show that the removal of the velocity ambiguity requires the random delays instead of lowering the average repetition rate significantly. It is noted that CSPPM combined signal has a super low probability of intercept and anti-jamming performance by deriving its ambiguous function. Unfortunately, the surveillance of this non-cooperative signal is a challenge problem for radar reconnaissance [5], [6]. Recent years, researchers concentrated on the analysis of the SPPM signal's generation [7], distance measurement methods [8] and properties [9]. Few literatures reported the pulse position prediction for the further signal sorting and tracking.

The purpose of this paper is to predict the combined signal's pulse occurrence time dependent on the live pulse position sequence, which can be treated as a discrete stationary random process in the presence of arbitrary time jitter. Inspired by that the stochastic time series can be predictable by auto-regressive/auto-regressive and moving-average (AR/ARMA) structure method [10], [11], we adopt them for the SPPM signal surveillance. As it is well known, the stationary sequence for the input of the AR/ARMA structure is of the essence. The classic solutions to the stationary transformation problem rely on the difference method and the logarithmic difference conversion (LDC) method [12]. However, they can not handle the certainty trend (CT) contained in the data sequence and be sensitive to timing jitters. Here, we propose a least square fitting (LSF) scheme deriving a stationary conversion to estimate the AR/ARMA model parameters. In contrast to LDC method, this allows a polynomial fitting of the pulse position sequence to eliminate the CT term and obtain a relatively stationary sequence. In addition, the initial frequency and chirp rate estimation is based on the traditional quick dechirp scheme. The experiment simulations illustrate the presented LSF scheme achieves a superior mean magnitude of relative error (MMRE) and the effect of intra pulse parameter estimation.

II. Signal Model

The CSPPM radar signal can be expressed as

$$s(t)=\frac{1}{\sqrt{N}}\sum_{n=1}^{N}Au\left(t-(n-1)T-\varepsilon_n\right)\mathrm{e}^{j[2\pi(f_0t+0.5kt^2)+\varphi_0]} \quad (1)$$

where

$$u(t)=\begin{cases}1/\sqrt{T_p}, 0\le t<T_p\\ 0, \quad otherwise\end{cases}$$

is the subpulse with the pulse width T_p and restricted to the signal interval T. N the pulse number, A the signal amplitude, f_0 the initial frequency, k the chirp rate, φ_0 the initial phase. The sequence $\{\varepsilon_n\}$ obeys a discrete-time random process indicating the pulse position modulation (PPM). Assuming it as the sequence of independent identically distributed (i.i.d) uniform random variables, the corresponding probability density function is modeled as

$$f(\varepsilon_n)=\begin{cases}\dfrac{1}{T-T_p}, & (n-1)T<\varepsilon_n<nT-T_p\\ 0 \quad, & otherwise\end{cases} \quad (2)$$

Note that, in general, $\{\varepsilon_n\}$ is nonstationary time series and has nonzero-mean.

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Suppose the signal $s(t)$ is contaminated with a stationary, independent, zero mean Gaussian white noise $w(t)$ to form the received $r(t)$. The observed pulse position of interest is expressed as

$$x_{pos}(n) = ((n-1)T + \varepsilon_n) f_s + \delta_n, \qquad n = 1, ..., N \quad (3)$$

where f_s is the sample frequency, δ_n the detection error sequence due to the noise. In the surveillance, the pulse position sequence $\{x_{pos}(n)\}$ is stochastic and monotonically increases. The intra pulse part is a chirp signal that is handled with a classic dechirp method.

III. The Prediction Scheme Based on AR and ARMA Model

A. Overview

In general, the short pulse position sequence has no apparent pattern in vague circumstance, and it is difficult to find a proper curve to fit it, but there is some links between the present value and its preceding values. Therefore, we can employ AR and ARMA models, achieving a great flexibility in the fitting of data series, to approximate and simulate it.

B. ARMA and AR Model

The general ARMA(p,q) process is defined as follows

$$x(n) + \sum_{i=1}^{p} a_i x(n-i) = v(n) + \sum_{j=1}^{q} b_j v(n-j) \quad (4)$$

where $\{v(n)\}$ is a white i.i.d Gaussian sequence with distribution $N(0, \sigma_v^{\ 2})$. p the order of AR progress, q the order of moving average (MA) progress, a_i and b_j the model parameters. In this framework, ARMA model will turn to AR model specifically when $q = 0$, which can be expressed as

$$x(n) = -\sum_{i=1}^{p} a_i x(n-i) + v(n) \quad (5)$$

Suppose we are given a stationary pulse position data sequence after the LSF conversion, $\{x(n), x(n-1), ...,$ $x(n-p+1)\}$, and it is desired to predict the next time position $x(n+1)$. Our objective of the pulse position prediction is then to estimate the AR and ARMA parameters from the information contained in the relationship of (4) and (5). The AR signal architecture satisfies the highly structured Yule-Walk equations

$$\begin{bmatrix} r_x(0) & r_x(-1) & \cdots & r_x(-p) \\ r_x(1) & r_x(0) & \cdots & r_x(-p+1) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(p) & r_x(p-1) & \cdots & r_x(0) \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} \sigma^2 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (6)$$

where $r_x(k) = E\{x(n)x(n+k)\}$ is the k th autocovariance lag and $E\{\bullet\}$ is the expectation operator. In fact, $r_x(k)$ is estimated by the N points observed data records. For the AR parameter estimation, they can be obtained by solving the set of YW equation and the efficient scheme dealing these recursively is Levinson-Durbin algorithm [13]. Moreover, for the ARMA parameter estimation, it has been shown the estimates can be separated as AR and MA model parameters estimation [10]. The major difficulty in AR coefficients accurate evaluation is that the larger lag k we employ and the worse autocovariance estimate $r_x(k)$ we will get. It is due to the limited amount of the position information available from the observed data series. Then, the modified YW equations could be extended to the overdetermined equations toward improving performance and can be written as

$$\begin{bmatrix} r_x(q) & r_x(q-1) & \cdots & r_x(q-p+1) \\ r_x(q+1) & r_x(q) & \cdots & r_x(q-p+2) \\ \vdots & \vdots & \ddots & \vdots \\ r_x(q+M-1) & r_x(p+M-2) & \cdots & r_x(q+M-p) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} r_x(q+1) \\ r_x(q+2) \\ \vdots \\ r_x(q+M) \end{bmatrix} \quad (7)$$

Note that, the equation number M is larger than p, the unknowns number. We can obtain $\hat{a}_1, \hat{a}_2, ..., \hat{a}_p$ in (7) by employing the recursive least square algorithm which is detailed in the previous section and obtain $b_1, b_2, ..., b_q$ via MA method [14].

IV. Analysis of the Data Series Preprocessing

The forecasting characteristics of radar pulse position are influential in the use of the appropriate methods. The premise condition of applying the AR and ARMA model prediction is that the data sequence must be stationary. Some nonstationary time series may manifest in common variation trend, however, they have no direct relevance relationship with each other and the output of the regressive filter has no meaning. The major schemes converting the nonstationary data into stationary ones fall into two categories: difference conversion and LDC. Unfortunately, they could not achieve an ideal performance as the preprocessing for the AR/ARMA model prediction. Here, we present a LSF scheme in part 4.2.

A. LDC Scheme

Let $\{x_{pos}(n)\}$ be the original sequence, the logarithm series $\{x_{\log}(n)\}$ can be generated as $x_{\log}(n) = 10\log_{10}(x_{pos}(n))$. The LDC sequence is defined as follows:

$$x_{d\log}(n+1) = x_{\log}(n+1) - x_{\log}(n), \quad n = 1, 2, ..., N-1 \quad (8)$$

To return the sequence to the original environment, the inverse LDC (ILDC) will be introduced. Therefore, LDC and ILDC is a pair of inverse data series operators. The ILDC process is given by

$$x_{pos}(n) = 10^{(\sum_{i_1=1}^{n} x_{d\log}(i_1))/10} \quad (9)$$

This LDC preprocessing method is suggested to deal with the data with stochastic trend. Unfortunately, it is not suitable for the nonstationary data with a CT term as detailed in Part B.

B. LSF Scheme

Assume that the stochastic process of one order AR is expressed as

$$Y_t = \alpha + \beta t + \gamma Y_{t-1} + u_t \quad (10)$$

where α , γ are the AR model coefficient, t the time trend, β the trend coefficient, u_t the Gauss white noise process. If $\gamma = 0$, $\beta \neq 0$, Y_t will exhibit a regular and monotonous shape following the negative or nonnegative term β . This kind of trend is called as CT. From (3), we known that the pulse position sequence of interest is a monotonic increasing procedure and contains the CT term, i.e., $\beta = Tf_s$.

By invoking the difference conversion method suitable for eliminate the stochastic trend, the result can be given as

$$\Delta Y = Y_t - Y_{t-1} = \beta + \gamma(Y_{t-1} - Y_{t-2}) + u_t - u_{t-1} \quad (11)$$

It is obvious that the CT term is not removed by this scheme. Here, we present a LSF method that dislodges the inherent trend and avoids the spurious regression through introducing time polynomial as trend variable, which is exploited to remove the β term. The procedure of the preliminary LSF includes the following steps.

Construct a mth degree fitting function $g(t) = p_1 t^m + p_2 t^{m-1} + \cdots + p_m t + p_{m+1}$, $m \le N_1$, where N_1 is the number of a live project sequence.

Minimize the sum of squares of the data deviation $\{g(t) - Y_t\}$,

$$\phi = \phi(p_1, p_2, ..., p_{m+1}) = \sum_{l=1}^{N_1} \left(\sum_{r=0}^{m} p_{m-r+1} t_l^{\,r} - Y_t \right)^2 \quad (12)$$

$$\frac{\partial \phi}{\partial p_{r1}} = 2\sum_{l=1}^{N_1} (\sum_{r=0}^{m} p_{m-r+1} t_l^{\,r}) t_l^{\,r1} - \sum_{l=1}^{N_1} Y_t t_l^{\,r1} = 0 \quad (13)$$

Solve (13) called as normal equations to obtain $(m+1)$ coefficients. Then, the modified sequence is $x_{lsf}(n) = x_{pos}(n) - g(n)$.

The corresponding inverse LSF (ILSF) is defined as $x_{pos}(n) = x_{lsf}(n) + g(n)$ .The LSF transformation can reduce the monotonous fluctuations in the sequences and have good stability. Especially in the case of radar pulse arrival position records, we would expect the LSF method to achieve a better forecasting than the LDC method. This is confirmed by our following simulation results.

C. Prediction Progress

The observed pulse position data are the records that are detected by the radar reconnaissance system. The investigation of the pulse position sequence used over the duration of once observation reveals that the general projects comprise less than 20 data. The next arrival position needs to be predicted with a finite sequence. From a radar reconnaissance system view, we consider the real time observation data as a sequence set or a local sequence, $\{x_{pos}(1), x_{pos}(2), ..., x_{pos}(N_1)\}$, $(N_1 = 20)$. Then, LSF scheme is acted on in terms of removing trend, leading to the production $\{x_{lsf}(1), x_{lsf}(2), ..., x_{lsf}(N_1)\}$. The aforementioned AR and ARMA model use these data series to predict the value of stage $N_1 + 1$, i.e., $\hat{x}_{lsf}(N_1 + 1)$. After ILSF conversion, it turns to $\hat{x}_{pos}(N_1 + 1)$. At the next moment, the local sequence will be $\{x_{pos}(2), x_{pos}(3), ..., x_{pos}(N_1 + 1)\}$, then do LSF transformation again to get the slide prediction value $\hat{x}_{pos}(N_1 + 2)$.

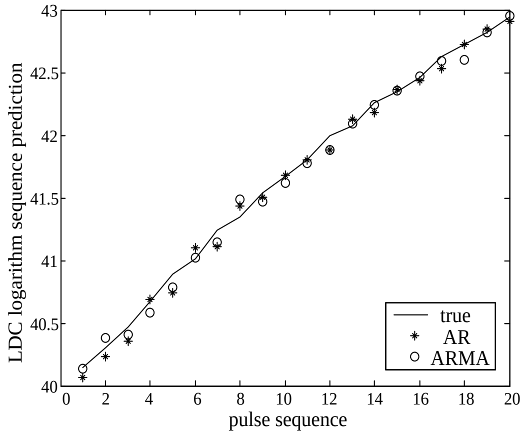
Function: GetPrediction, obtain the prediction values from a set of global sequence.The global number N=40,the local number N1 =20.
Input: a set of global sequence
Output: (N-N1) prediction values
1) for each k from 20 to (40-1)
2) $X\_local = \{x_{pos}(k-19), x_{pos}(k-18), ..., x_{pos}(k)\}$
3) $X_{lsf} = polyfit(X\_local)$
4) $\hat{x}_{lsf\_ar}(k+1) = AR\_pre(X_{lsf})$
5) $\hat{x}_{lsf\_arma}(k+1) = ARMA\_pre(X_{lsf})$
6) $\hat{x}_{ar}(k+1) = inverse\_polyfit(\hat{x}_{lsf\_ar}(k+1))$
$\hat{x}_{arma}(k+1) = inverse\_polyfit(\hat{x}_{lsf\_arma}(k+1))$
7) $MMRE1(k+1) = |\frac{\hat{x}_{ar}(k+1) - x_{pos}(k+1)}{x_{pos}(k+1)}|$
$MMRE2(k+1) = |\frac{\hat{x}_{arma}(k+1) - x_{pos}(k+1)}{x_{pos}(k+1)}|$
8) end for

Figure 1. Prediction procedure

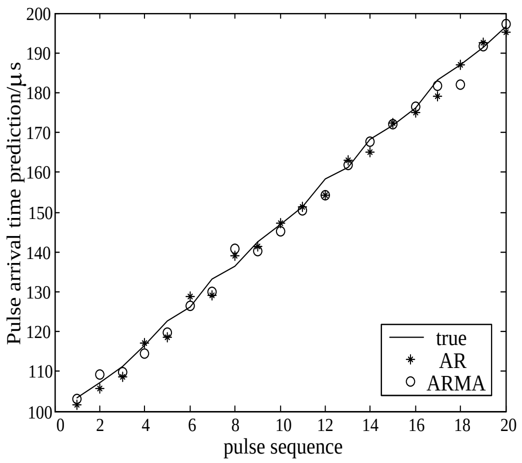
For ease of description, we denote the LSF transformation as $x_{lsf} = polyfit(x_{pos})$, the AR and ARMA forecasting procedure by a function called as AR_pre and $ARMA\_pre$. The procedure for obtaining the optimum estimates is summarized in Fig. 1.

V. Experiments and Analysis

In order to clarify the behavior of the proposed LSF preliminary method for AR/ARMA model prediction, which has been explored to remove the CT term, the prediction performance via the LSF algorithm was compared to the performance via the LDC algorithm. 50 Monte Carlo trials were performed adopting the detected pulse position sequence of a chirp & SPPM signal. Among them, the global data series $N = 40$ and the local data series $N_1 = 20$. For each Monte Carlo trail, the SNR was set to 5dB. f_s=100 MHz , f_0=10 MHz , k=5×10^{12} Hz/s , $T = 2$ μs , $T_p = 1$ μs , $\varphi_0 = 0$ rad , $\varepsilon_n \in [(n-1)T, (nT - T_p)]$. The arrival position, $x_{pos}(n)$, of PPM signal pulses can be obtained via many standard methods, such as energy detection algorithm [15]. The local 20 data series are treated as the training data to forecast the next one, and then go on with a slide prediction.



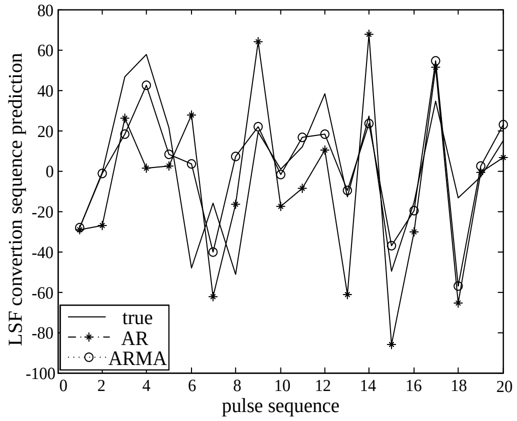
(a) The logarithm sequence prediction



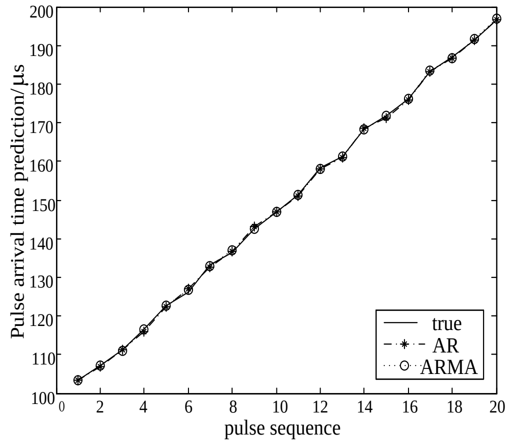
(b) The pulse position prediction

Figure 2. AR and ARMA model prediction via LDC scheme.

According to the data series, AR(13) and ARMA(2,4) architectures are chosen on basis of AIC criterion. Fig. 2 (a) provides an illustrative depiction of the outputs of the AR/ARMA filters, of which the input is the LDC sequence. It plots the logarithm term estimates, i.e., $\hat{x}_{\log}(n)$. In the absence of a regular pattern, the LSF conversion sequence prediction through AR(13)/ ARMA(2,4) by fitting the 6th order fitting polynomial is presented in Fig. 3 (a). In contrast to the LDC method, it can be found that the observed sequence is stationary without CT. Fig. 2 (b) and Fig. 3 (b) portrays the global data (from $\hat{x}_{pos}(21)$ to $\hat{x}_{pos}(40)$) prediction performance via LDC and LSF, respectively. It is evident that the LDC method deteriorates when the difference logarithm value is not predicted very accurately. On one hand, the logarithm operator causes the error expansion; on the other hand, the CT term is not eliminated by the LDC method. From Fig. 3 (b), the LSF scheme achieves a satisfactory result.



(a) LSF conversion sequence prediction



(b) The pulse position prediction

Figure 3. AR and ARMA model prediction via LSF scheme.

A comparative study of the forecasting performance is provided in Table I and Table II. For ease of observation and comment, the last ten prediction values were picked out. In this study, we use the residual and mean magnitude of relative error (MMRE) as evaluation measures.

The residual and MMRE are defined as follows:

$$\text{residual}(n) = \frac{1}{S}\sum_{s=1}^{S}|x_{pos}(n) - \hat{x}_{pos}(n)| \tag{14}$$

$$\text{MMSE}=\frac{1}{S}\sum_{s=1}^{S}|\frac{x_{pos}(n) - \hat{x}_{pos}(n)}{x_{pos}(n)}| \tag{15}$$

where S is the Monte Carlo trial. AR and ARMA architectures forecasting are employed in the experiment as shown in Table I and Table II, respectively. It is apparent from the comparison the LSF scheme delivers a better performance than the LDC method. The superior residual and MMSE imply that the LSF method has better consistency and stability on different forecasting methodologies. We also observe that compared with LDC, the LSF's MMRE improvement is about 70% to 97% for AR prediction, and about 42% to 99% for ARMA prediction.

In our experiment, AR and ARMA models having low orders are explored due to the limited amount of the live observation data sequence.

TABLE I MMRE of AR PREDICTION ADOPTING THE LDC AND LSF METHOD

Data sequence	LSF		LDC		LSF's MMRE improvement (%)
	residual	MMRE	residual	MMRE	MMRE
$x_{pos}(31)$	5.12	0.0009	36.82	0.0061	86.09
$x_{pos}(32)$	14.30	0.0023	115.98	0.0185	87.67
$x_{pos}(33)$	5.50	0.0008	52.34	0.0081	89.48
$x_{pos}(34)$	23.39	0.0035	78.49	0.0119	70.20
$x_{pos}(35)$	3.64	0.0005	109.10	0.0160	96.66
$x_{pos}(36)$	0.51	0.0001	18.72	0.0027	97.27
$x_{pos}(37)$	10.01	0.0014	129.65	0.0178	92.28
$x_{pos}(38)$	21.60	0.0029	79.73	0.0107	72.92
$x_{pos}(39)$	4.58	0.0006	90.61	0.0119	94.95
$x_{pos}(40)$	2.09	0.0003	42.69	0.0055	95.11

TABLE II MMRE OF ARMA PREDICTION ADOPTING THE LDC AND LSF METHOD

Data sequence	LSF		LDC		LSF's MMRE improvement (%)
	residual	MMRE	residual	MMRE	
$x_{pos}(31)$	2.08	0.0003	16.12	0.0027	87.08
$x_{pos}(32)$	16.31	0.0026	76.64	0.0122	78.72
$x_{pos}(33)$	9.14	0.0014	50.84	0.0078	82.02
$x_{pos}(34)$	0.38	0.0001	58.35	0.0088	99.36
$x_{pos}(35)$	16.09	0.0024	27.74	0.0041	42.01
$x_{pos}(36)$	0.49	0.0001	38.02	0.0054	98.70
$x_{pos}(37)$	9.33	0.0013	168.74	0.0231	94.47
$x_{pos}(38)$	1.30	0.0002	15.85	0.0021	91.81
$x_{pos}(39)$	9.47	0.0012	19.98	0.0026	52.59
$x_{pos}(40)$	5.31	0.0007	16.15	0.0021	67.10

Considering the real time requirement of radar reconnaissance, the number of the model order does not change as the local slide data change. It influences the prediction performance to a certain extent. However, the result via LSF is still satisfactory. In addition, the MMRE of AR prediction algorithm is superior to that of ARMA. Moreover, the prediction by AR modeling is much simpler, and the MA terms can be ignored if we suppose the decimation filtering is an ideal lowpass filter [16].

The Fig. 4 and Fig. 5 provide an illustrative depiction of the intra pulse parameters estimation, using the quick dechirp method and cyclic autocorrelation[17] approach presented as "Quick D" and "Cyclic A" in the figures, respectively. It exhibits that the quick dechirp method achieves better estimation accuracy with respect to the initial frequency, and the similar performance to the chirp rate. It is due to the limited pulse width and underserved cyclic statistics for the cyclic autocorrelation approach deterioration. Therefore, we adopt the quick dechirp method for CSPPM signal.

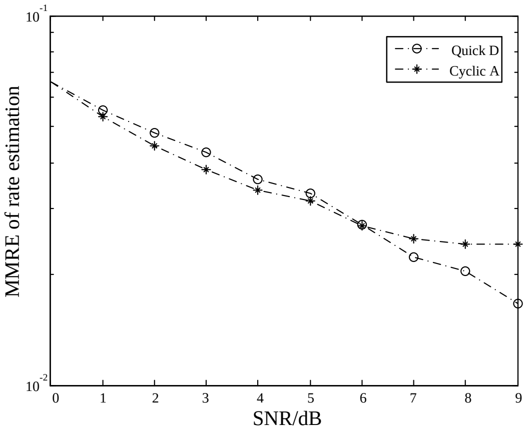


Figure 4. The chirp rate estimation

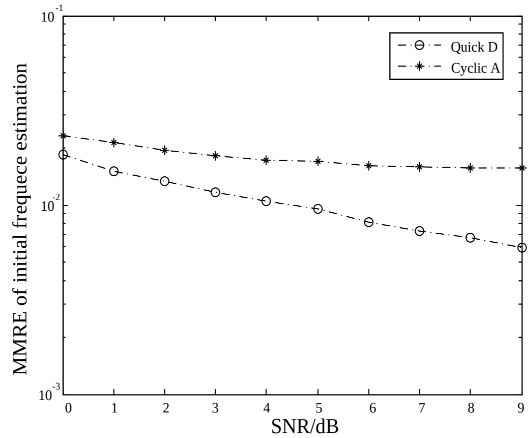


Figure 5. The initial frequency estimation

VI. DISCUSSION AND CONCLUSION

From the results, the quick dechirp approach is employed for parameter estimation. In addition, it is apparent that the CSPPM signal's pulse position transformation sequence via the presented LSF scheme obeys an AR/ARMA process. The LSF scheme is presented in the preliminary process of AR/ARMA forecasting approach to obtain a stationary sequence. Compared with LDC, its performance shows significant improvement for radar pulse position prediction, which is due to the CT term elimination. Our LSF approach with AR/ARMA achieving a low MMSE plays an important role in further radar signal sorting and tracking. We will continue to investigate the calculation reduction for better radar reconnaissance application.

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