Parameter Estimation of LFM Signal in Low Signal-to-Noise Ratio Using Cross-Correlation Function

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Abstract. *The pulse with intra-pulse modulation plays an important role in the design of radar systems. The first class of the signals type is the linear frequency modulation technique. The linear frequency modulation is used to resolve range resolution problems. This paper provides a new algorithm for detecting linear frequency modulation signals at a low signal-to-noise ratio. The core idea of the proposed method is firstly to analyse the linear frequency modulation signals via Fast Fourier Transform; and then to accumulate all energy to achieve signal detection using cross-correlation methods. The proposed algorithm showed better results in comparison with current algorithms, which are used to estimate the parameters of the linear frequency modulation signals at a low signal-to-noise ratio.*

Keywords

Auto-correlation function, cross-correlation function, Fast Fourier Transform, linear frequency modulation, short-time Fourier transform, signal-to-noise ratio.

1. Introduction

Intentional intra-pulse phase or frequency modulation is quite common in modern radar. Perhaps, most radars of recent design use such modulation for compression purposes. The most often used modulations are Linear Frequency Modulation (LFM) and binary phase reversals, sometimes in the form of Barker Code [1] and [2]. For the Low Probability of Intercept radar (LPI), it is important to recognise and estimate the parameters of the LFM signals fast and precisely.

Many methods are used to detect and analyse LFM signals, such as Radon-Wigner Transformation and Radon-Ambiguity Transformation [3]. These methods can give an accurate estimate of the LFM parameters, but the amount of computation is quite large since it requires a two-dimensional search. Other methods could be also used to detect and estimate the parameters of LFM signals, which are based on smoothed instantaneous energy such as using the Hamming, Rectangular, Hanning and Blackman window functions. To achieve up to 100 percent probability of correct parameters estimation, the value of SNR ≥ -4 dB [4] is required. In [5], the maximum likelihood method has the best estimation performance, but involves extensive calculation due to the two-dimensional search. Moreover, it may converge to the local extreme. In [6], the dechirp parameter estimation method needs less calculation, but its estimation accuracy and resolution are low, and its anti-jamming ability is insufficient. The other method used for detection and parameter estimation of LFM signals was proposed in [7]. This method is based on Deep Convolutional Neural Network, where the required value of SNR to obtain the perfect probability of correct parameter estimation is SNR ≥ -6 dB. In [8], the Time Reversal and Fractional Fourier Transform (TR-FrFT) method is extremely accurate for detecting and estimating the parameters of the LFM signal. The lowest value of SNR to achieve up to 90 % probability of detection is SNR ≥ -15 dB.

Although these methods can effectively be used to detect and estimate the parameters of LFM signals, they still require extensive searching, which significantly reduces the estimation speed. To deal with the above-mentioned disadvantages, this paper proposes a new algorithm to obtain a fast and accurate parameter estimation of the LFM signal in low SNR. The main idea of this algorithm is employed in a cross-correlation function between two signals to find the LFM signals at the lower SNR. The paper focuses only on detecting LFM signal in mixture signals and noise at SNR ≤ -15 dB. Firstly, the reference LFM signals are generated in a wide frequency bandwidth. Then, the cross-correlation function is calculated between an unknown and reference LFM signal via Fast Fourier Transform (FFT). Finally, the peak value of the cross-correlation function is found to detect and estimate the parameters of the unknown LFM signal and compute the accuracy of this method.

A theoretical description of the LFM waveform is presented in Sec. 2. In Sec. 3. , the algorithm steps are proposed for estimating the LFM parameters. In Sec. 4. , the simulation results are presented - test results with different levels of SNR and different chirp rates of the LFM signals to determine the minimum value of SNR at which the method is still able to detect LFM signals and estimate their parameters. And finally, in Sec. 5. , the main conclusions are drawn from the summarised simulation results.

2. Theoretical Description of LFM Signal

Frequency or phase modulated signals can be used to achieve much wider operating bandwidths. The LFM is commonly used where the frequency is swept linearly across the pulse either upward (up-chirp) or downward (down-chirp). The matched filter bandwidth is proportional to the sweep bandwidth and independent of the pulse width. Figure 1 shows a typical example of an LFM signal. The pulse width is τ and the bandwidth is B. The LFM up-chirp instantaneous phase can be expressed by the following equation [2]:

$$\psi(t) = 2\pi\left(f_0 t + \frac{\mu}{2}t^2\right), \quad -\frac{\tau}{2} \leq t \leq \frac{\tau}{2}, \tag{1}$$

where f_0 is centre frequency of LFM signal and $\mu = \frac{2\pi B}{\tau}$ is the LFM coefficient. Thus, the instantaneous frequency is defined as follows:

$$f(t) = \frac{1}{2\pi}\frac{d}{dt}\psi(t) = f_0 + \mu t, \quad -\frac{\tau}{2} \leq t \leq \frac{\tau}{2}. \tag{2}$$

Similarly, the down-chirp instantaneous phase and frequency are given respectively by:

$$\psi(t) = 2\pi\left(f_0 t - \frac{\mu}{2}t^2\right), \quad -\frac{\tau}{2} \leq t \leq \frac{\tau}{2}, \tag{3}$$

$$f(t) = \frac{1}{2\pi}\frac{d}{dt}\psi(t) = f_0 - \mu t, \quad -\frac{\tau}{2} \leq t \leq \frac{\tau}{2}. \tag{4}$$

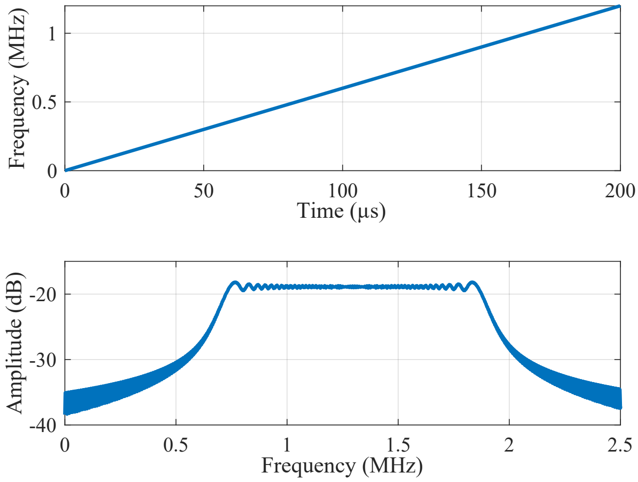


Fig. 1: Time-frequency characteristics and amplitude spectrum of chirp-up LFM signal.

A typical LFM signal can be expressed by a omplex nation as follows:

$$s_1(t) = \mathrm{rect}\left(\frac{1}{\tau}\right)\exp\left(j2\pi\left(f_0 t + \frac{\mu}{2}t^2\right)\right), \tag{5}$$

where rect $\left(\frac{1}{\tau}\right)$ denotes a rectangular pulse of width.

Then, Eq. (5) can be written as follows:

$$s_1(t) = \exp\left(j2\pi f_0 t\right) s(t), \tag{6}$$

where $s(t)$ is the complex envelop function of $s_1(t)$ and defined by the following equation:

$$s(t) = \mathrm{rect}\left(\frac{1}{\tau}\right)\exp\left(j\frac{\mu}{2}t^2\right). \tag{7}$$

The spectrum of signal $s_1(t)$ is determined from its complex envelope $s(t)$. The complex exponential term in Eq. (6) introduces a frequency shift around the value of the centre frequency f_0. Taking the FFT of $s(t)$ yields, we get:

$$S(\omega) = \int_{-\tau/2}^{\tau/2} \exp\left(\frac{j2\pi\mu t^2}{2}\right) e^{-j\omega t} dt. \tag{8}$$

The time-frequency characteristic and spectrum of the typical chirp-rate LFM signal are shown in Fig. 1.

3. Proposed Method

In signal processing [3], the cross-correlation function is a measure of similarity of two series as a function of displacement of one relative to other. This method is applied in pattern recognition, single particle analysis. Thus, the cross-correlation function between two signals $x(t)$ and $g(t)$ is expressed by the equation:

$$R_{xg}(t) = \int_{-\infty}^{\infty} x^*(\tau)g(t+\tau)d\tau, \qquad (9)$$

where $R_{xg}(t)$ is the cross-correlation function between two signals, $x^*(\tau)$ is the complex conjugate of $x(t)$, $g(t+\tau)$ is the second signal at $t+\tau$ and τ is the delay time. The cross-correlation function measures the similarity between two signals. Both, the peak value of $R_{xg}(\tau)$ and the distribution around this peak are an indication of how good this similarity is. The cross-correlation function can be computed via FFT as follows:

$$R_{xg}(t) = F^{-1}\left\{X^*(\omega)G(\omega)\right\}, \qquad (10)$$

where $X(\omega)$ and $G(\omega)$ are the spectra of the signals $x(t)$ and $g(t)$, $X^*(\omega)$ is the complex conjugate of $X(\omega)$ and F^{-1} is the inverse FFT. When $x(t) = g(t)$, we get the autocorrelation of the signal, which is defined by the equation:

$$R_x(t) = \int_{-\infty}^{\infty} x^*(\tau)x(t+\tau)d\tau, \qquad (11)$$

where $R_x(t)$ is the auto-correlation function of signal $x(t)$, $x^*(\tau)$ is the complex conjugate of $x(t)$ at τ, and $x(t+\tau)$ is the signal $x(t)$ at $t+\tau$. In an auto-correlation, which is the cross-correlation between the signal and itself, there will always be a peak at the lag of zero and its value will be the signal energy.

In Fig. 2(a) and Fig. 2(b), the results of the cross-correlation functions between two signals with the same pulse width at different levels of SNR are shown. The blue line is the Auto-Correlation Function (ACF) and the red line is the Cross-Correlation Function (CCF) between two signals that have different chirp rates (i.e. frequencies). The simulated results suggest that when two signals have the same frequency, their CCFs have the highest value at the center of the pulse. Figure 2(c) and Fig. 2(d) show the results of the CCF between two signals at different levels of SNR, which have the same frequency and different pulse widths. The simulated results confirmed that when two signals have the same pulse width τ, their CCF have their highest value at $t = 0$ s. From these results, we propose a new algorithm to detect and estimate the parameters of the LFM signal based on the theory of the cross-correlation functions between two signals.

The algorithm divides into two estimators. The first one is used for detecting and measuring the chirp rate μ and the center of pulse width t_c of the LFM signal. The second one is used for estimating the pulse width τ and the Time Of Arrival (TOA) of the LFM signal. The basic idea behind the algorithm procedure is written below and the simulation parameters are given in Tab. 1.

- *Step 1*: Generating reference LFM signals $s(t)$ on wide frequency bandwidth B and the same pulse width τ. The reference LFM signal is expressed by the equation:

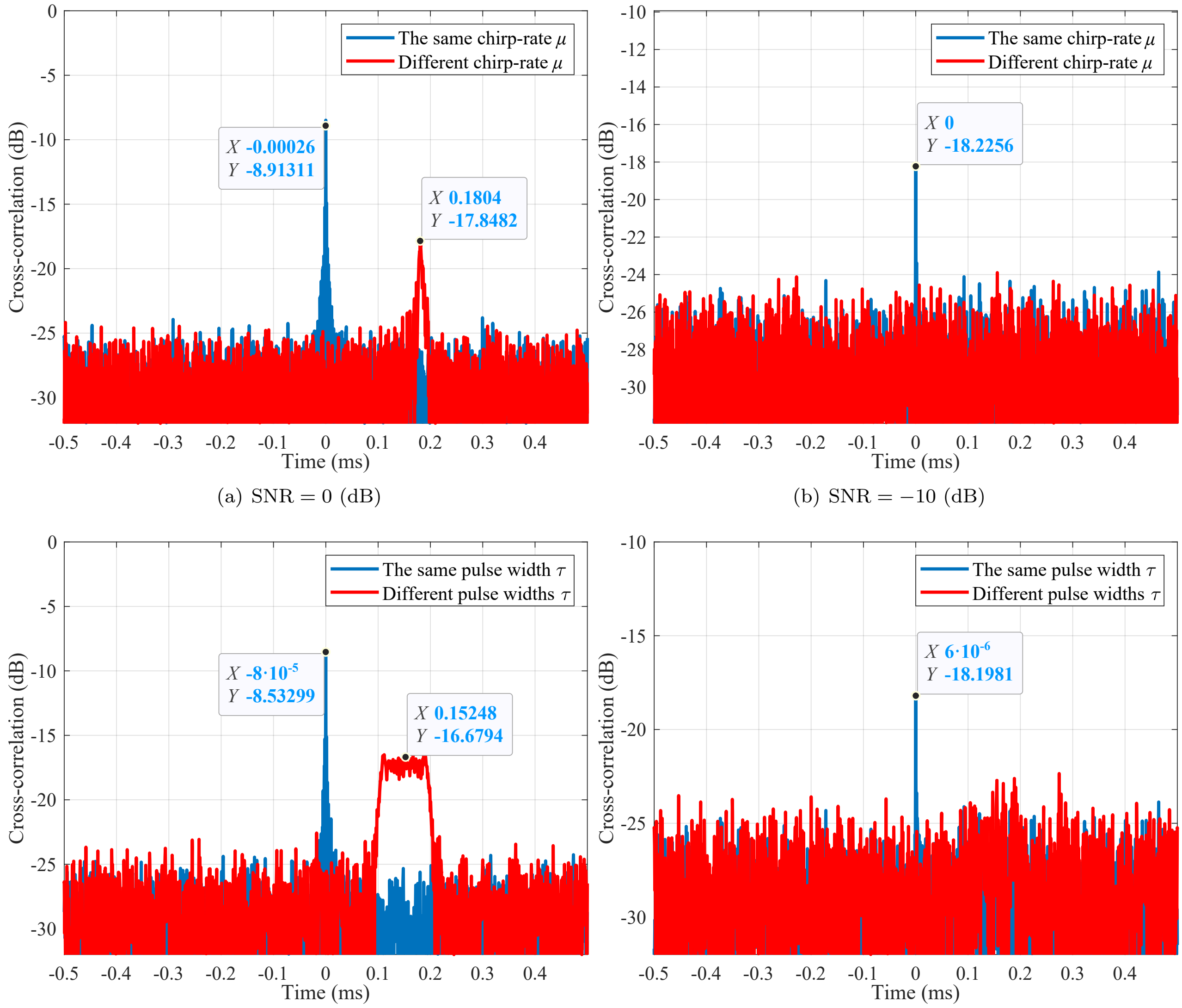
$$s(t) = \left[s_1(t), s_2(t), s_3(t), \ldots, s_{n-1}(t), s_n(t)\right], \qquad (12)$$

  where n is the number of LFM signals.

- *Step 2*: Calculating spectrum $S_u(\omega)$ and $S(\omega)$ of the unknown $s_u(t)$ and reference LFM signal $s(t)$.
- *Step 3*: Calculating cross-correlation function between the unknown and reference signals via FFT using Eq. (11).
- *Step 4*: Finding out the peak value of the cross-correlation function to detect and estimate chirp-rate μ and center of pulse width t_c of the unknown LFM signals.
- *Step 5*: Generating new reference LFM signals $s_n(t)$ at known chirp-rate with an expanding pulse width around t_c, which are calculated in step 4.
- *Step 6*: Calculating FFT of $s_n(t)$. Then calculating CCF between unknown $s_u(t)$ and $s_n(t)$.
- *Step 7*: Finding out the peak value of the CCF to estimate pulse width τ of $s_u(t)$. Finally, calculating TOA of $s_u(t)$.

Figure 3 shows a plot of the time-frequency characteristics of the unknown (red line) and reference LFM signals (blue line). In order to estimate the chirp-rate μ of the unknown LFM signal, it is only necessary to determine the index of reference signal, which has a maximum value of CCF with the unknown LFM signal. The same case with estimating t_c it is needed to determine the maximum value of CCF in the time domain.

The CCF of the unknown and first reference LFM signals is shown in Fig. 4(a). The maximum value of CCF versus the index (i.e., the chirp-rates of reference LFM signals) are shown in Fig. 4(b). It shows that the highest value of the CCF is $R(t) = 36.61$ dB at chirp-rate $\mu = 6$ GHz·s^{-1}. It means that the unknown LFM signal is close to a reference signal which have the chirp-rate $\mu = 6$ GHz·s^{-1}. In Fig. 4(c) it seen that the maximum of CCF is at time $t = 300$ µs. It means that the center of pulse with of the unknown LFM signal is



(a) SNR $= 0$ (dB)

(b) SNR $= -10$ (dB)

(c) SNR $= 0$ (dB)

(d) SNR $= -10$ (dB)

Fig. 2: CCF of between two signals at different levels of SNR: (a) SNR $= 0$ (dB), (b) SNR $= -10$ (dB) with different chirp-rate, (c) SNR $= 0$ (dB), (d) SNR $= -10$ (dB) with different pulse widths.

Tab. 1: Simulation parameters.

	Parameters	**Value**
Unknown LFM signal	SNR (dB)	-10
	Pulse width τ (µs)	200
	Time Of Arrival TOA (µs)	200
	Chirp-rate μ (MHz·s^{-1})	6000
First reference LFM signals	Pulse width τ (µs)	300
	Chirp-rate μ (MHz·s^{-1})	$1000 \div 12{,}000$
	Number of the LFM signals n	100
Second reference LFM signals	Pulse width τ (µs)	$0 \div 600$
	Chirp-rate μ (MHz·s^{-1})	6000
	Number of the LFM signals n	100

$t_c = 300$ µs. In other words, the chirp-rate μ and center of pulse width t_c of the unknown LFM signal was estimated by using the first estimator ($\mu = 6$ GHz·s^{-1}, $t_c = 300$ µs). The next step of this paper is to generate a new reference LFM signals at the estimated chirp-rate with expanding pulse width around $t_c = 300$ µs then to calculate the new CCF between the unknown and these reference signals. As was the case above with estimating chirp-rate μ and t_c of the unknown LFM signal, only the index of reference signal needs to

Tab. 2: Estimated parameters of LFM signal at SNR $= -10$ dB by running the system for 200 loops.

Parameters	Simulation values	Estimated values	Relative error (%)	RMSE (-)
μ (MHz·s^{-1})	6000	6011.52	0.368	0.022
τ (µs)	200	200.364	0.149	0.448
t_c (µs)	300	299.818	0.061	0.382
TOA (µs)	200	199.636	0.182	0.588

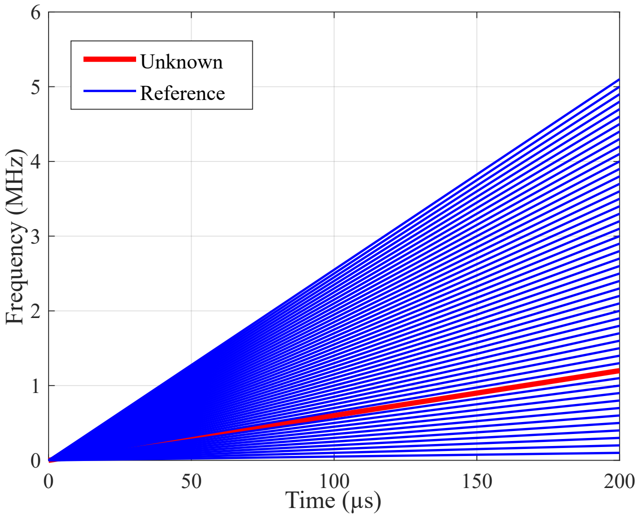


Fig. 3: Time-frequency characteristics of the unknown and reference LFM signals.

be determined with the highest value of CCF with the unknown signal. The CCF between the unknown and second reference signals in 3D as shown in Fig. 5(a). Figure 5(b) shows the peak values of the CCF versus the index (i.e., pulse widths of reference LFM signals). It shows that the maximum value of CCF is $R(t) = 35.73$ dB at the pulse width $\tau = 198$ µs. From these estimated parameters, the TOA is calculated by the equation:

$$\mathrm{TOA} = t_c - \frac{\tau}{2} = 300 - \frac{198}{2} = 201 \ \mu\mathrm{s}. \quad (13)$$

The estimated parameters of the unknown LFM signal at SNR $= -10$ dB is given in Tab. 2. According to the simulated results, a new method was proposed for detecting and estimating the parameters of the LFM signal in low SNR. In the next section of this paper, the effect of this method needs to be examined with different levels of SNR, different LFM signals in comparison with current methods. In addition, the minimum value of SNR should be determined at which this method is suitable to obtain the perfect probability of correct parameter estimation ($P_{ce} \geq 90$ %) on signal analysis.

4. Simulation Results

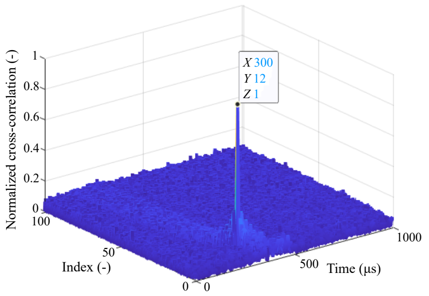
In the previous, the theoretical description of the proposed method was explained. In this section, the proposed method is evaluated with different simulation parameters by using the program MATLAB. In order to verify the performance of this method, Monte Carlo simulation is performed for all tests of LFM signals by running the system for 500 loops for an SNR range from -26 dB to 0 dB and the probability of correct estimation P_{ce} at the end of 500 loops. All tests are performed on the condition that the chirp-rate and pulse width of the unknown LFM signal is within the observed chirp-rate and pulse width range of reference LFM signals.

The first simulation determines the required value of SNR at which the first estimator is still suitable for detecting the LFM signal, i.e., for estimating its chirp-rate μ. The chirp-rate of the unknown LFM signal was set at the minimum $\mu_{\min}$, centre μ_c and maximum value $\mu_{\max}$ of the chirp-rate of the reference LFM signals. Figure 6 shows a plot of time-frequency characteristic of the test and reference LFM signals.

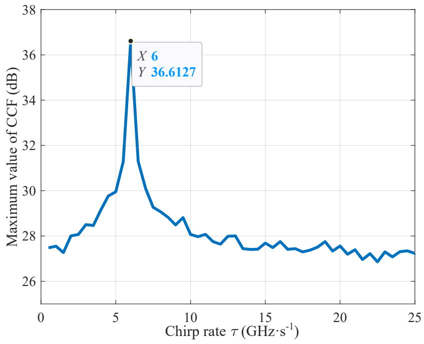
Figure 7 shows a plot of probability of correct estimation versus the levels of SNR of the test LFM signals at special chirp-rate. The simulated results show that the accuracy of the method directly depends on the chirp-rate μ of the test LFM signal. At the same value of $SNR = -20$ dB, this method gives the best results ($P_{ce} = 97.24$ %) for the second test LFM signal (its chirp-rate is equal to the centre of chirp-rate of reference signals, red line), followed ($P_{ce} = 92.20$ %) by the third test LFM signal (black line). The lowest accuracy ($P_{ce} = 0$ %) is for the first test LFM signal (its chirp-rate is equal to the minimum chirp-rate of reference signals, blue line).

Similar to the first step, in this step the minimum value of SNR is determined where the method is still suitable for obtaining a perfect probability of correct estimation ($P_{ce} \geq 95$ %) for centre of pulse width t_c for all test signals. The accuracy of method for analysing t_c versus SNR is shown in Fig. 8(a). It is seen that irrespective of the time parameter being estimated, at the same value of SNR $= -20$ dB, the highest accuracy ($P_{ce} = 90.39$ %) is for the second test signal (red line), followed ($P_{ce} = 87.30$ %) by the third test signal (black line). The lowest accuracy ($P_{ce} = 86.41$ %) is for first test signal (blue line).

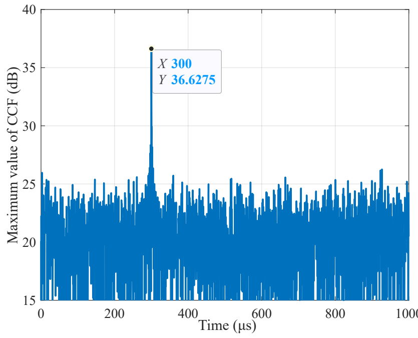
Altogether, the required value of SNR is SNR ≥ -18 dB at all chirp-rate of the unknown LFM signal in order to obtain a perfect probability of correct estimation ($P_{ce} \geq 95$ %) for analysing chirp-rate and centre of pulse width t_c of LFM signals. The same



(a) 3D.

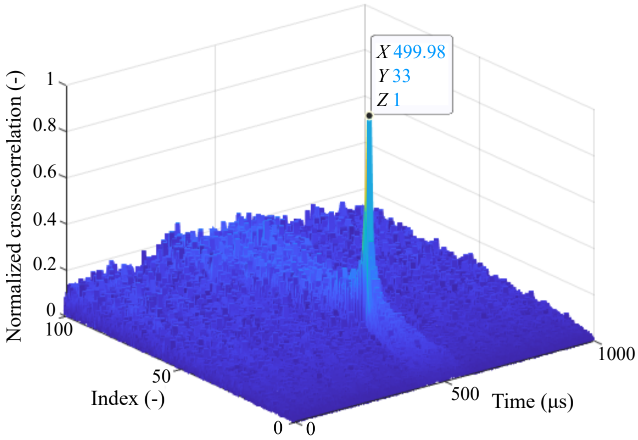


(b) Peak value of CCF versus chirp-rate of reference LFM signals.

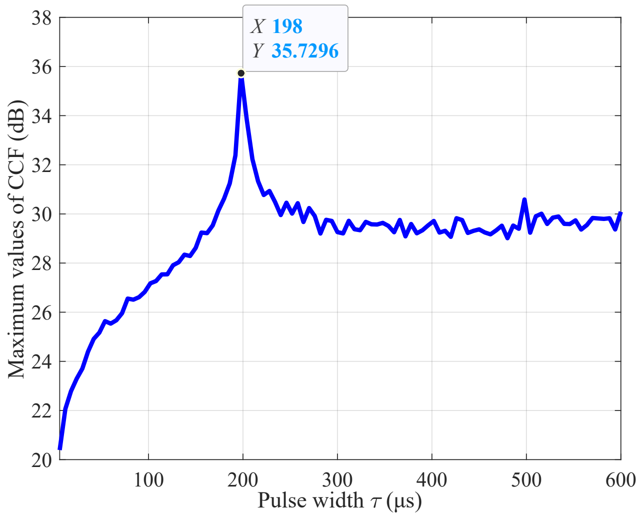


(c) Peak value of CFF versus time.

Fig. 4: CFF between unknown and first reference LFM signals: (a) 3D, (b) peak value of CFF versus frequency of reference LFM signals, (c) peak value of CFF versus time.



(a) 3D.



(b) CCF versus pulse widths.

Fig. 5: CCF between unknown and second reference LFM signals: (a) 3D, (b) CCF versus pulse widths.

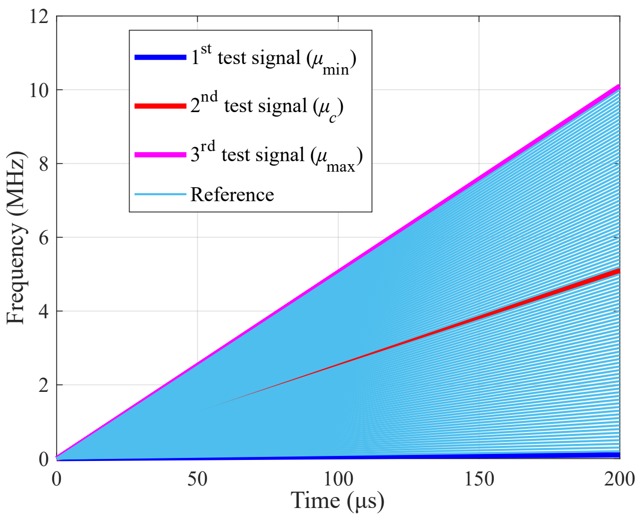


Fig. 6: Time-frequency characteristics of LFM signals.

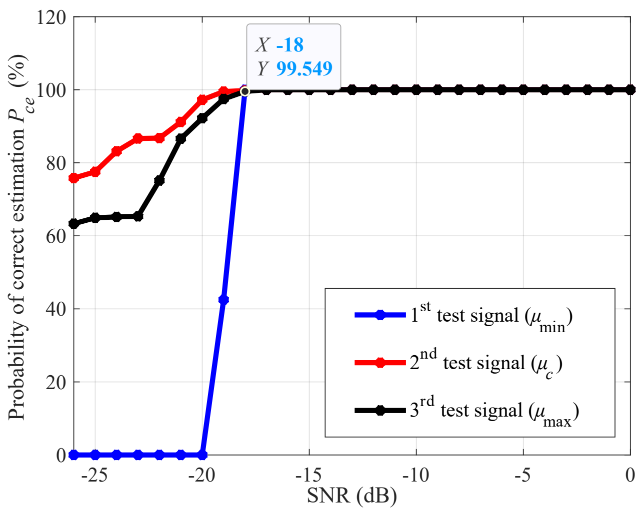
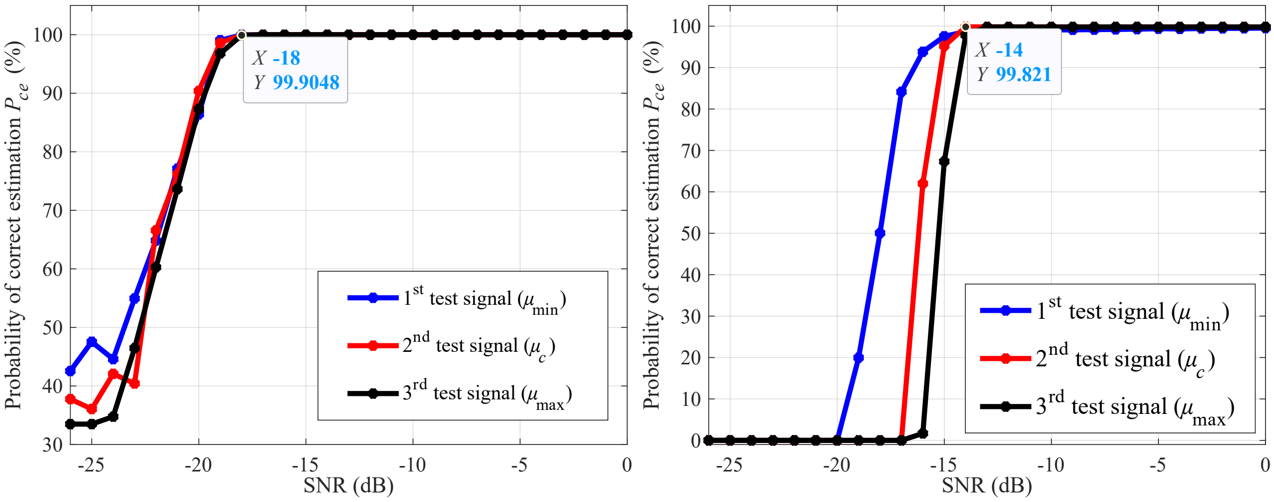


Fig. 7: Probability of correct estimation depends on SNR.



(a) Centre of pulse width estimation. (b) Pulse width estimation.

Fig. 8: Probability of correct estimation depends on SNR: (a) centre of pulse width estimation, (b) pulse width estimation.

case is SNR ≥ -14 dB for all test signals when estimating the pulse width τ of the unknown signal with only difference being the value of SNR to achieve a perfect probability of correct estimation ($P_{ce} \geq 95$ %) (see Fig. 8(b)).

The last step in this section is examined the effect of the proposed method in comparison with the other methods for analysing LFM signals. The parameters of the unknown LFM are shown in Tab. 1. The probability of detection of each method is shown in Fig. 9.

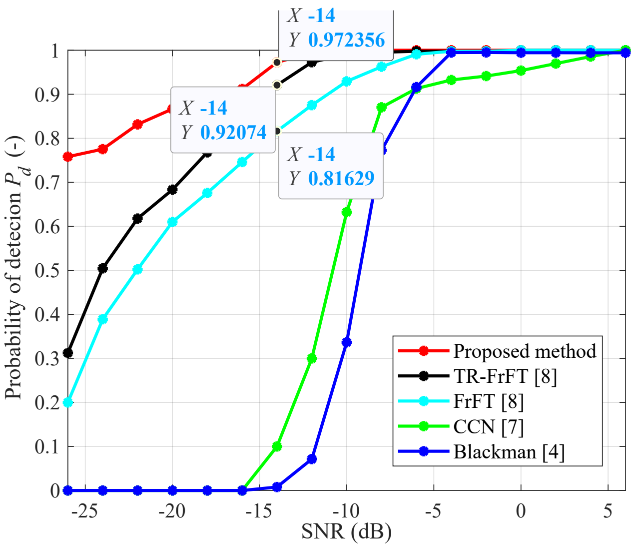


Fig. 9: Probability of detection of methods depends on SNR.

Figure 9 shows that the proposed method demonstrated a higher result in comparison with other methods for detecting the LFM signal in mix signals and noise. At the same value of SNR $= -14$ dB, our method gives the best probability of detecting the LFM signal ($P_d = 97.23$ %), followed by TR-FrFT ($P_d = 92.07$ %), FrFT ($P_d = 81.63$ %) in [8] and CCN ($P_d = 10$ %) in [7]. The lowest probability of detection is for method in [4]. The summarised simulation results in this section confirmed that the proposed method is more effective than other methods in [4], [7] and [8]. The required value of SNR to obtain a perfect probability for detecting the LFM signal ($P_d \geq 95$ %) is SNR ≥ -15 dB. However, the effect of the proposed method depends on the number of reference signals. The larger number of reference signals gives better results but has problems with the number of calculations and running-time of all system. The next paper will be presented the optimization of this method for analysing real LFM signals.

5. Conclusion

This paper presents a new, fast, and highly accurate detection and parameter estimation method based on the CCF for LFM signals in low SNR. Firstly, the cross-correlation between the unknown signal and reference signals was designed to determine the chirp rate μ and centre of pulse width t_c of the unknown signal. This was then used to estimate the pulse width τ of the unknown signal. This paper examined the effect of the proposed method for LFM signals with different chirp rate for a SNR range from -26 dB to 0 dB. The simulation results show that the minimum value of SNR is SNR ≥ -18 dB in order to obtain a perfect probability of detection ($P_d \geq 95$ %) for all test LFM signals and the proposed method performed higher accuracy in comparison with other methods (in [4], [7] and [8]). It confirmed that this method is suitable for detecting and estimating the parameters of LFM signal in an ultra-low SNR. Therefore, further studies are needed to optimise this method in order to reduce the number of reference LFM signals and the running time of all system. In addition, the proposed method can be used as an off-line signal detection and analysis and the estimated parameters can be used as an input to the classifier network.

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Author Contributions

V.M.D., J.V. and P.H. developed the theoretical formalism, performed the numerical simulations. V.M.D., P.J. and N.G.P. contributed to the final version of the manuscript. J.V. supervised the project.

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