UAV target detection and parameter estimation in non-homogeneous clutter

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Abstract: Aim at the problem of UAV target detection and parameter estimation in non-homogeneous clutter with STLFMCW radar, a SK-CFAR detector is proposed based on the local spectrum refinement. By using zoom-FFT, the two-dimensional spectrum of the received signal is extracted for local template matching. Subsequently, the two-dimensional SK-CFAR detector and CLEAN technique are applied to decide whether there exist some targets in the region of interest. Compared with Radon–Fourier transform (RFT) and moving target detection (MTD), the proposed estimator based on local speed compensation is a good choice for the trade-off of high performance and low computational load even though the input signal-to-clutter ratio approaches to ~24 dB.

1 Introduction
LFCMCW radar transmits continuous waveform with sawtooth LFCMCW or triangular-shaped (STLFMCW) linear frequency modulation [1]. This paper mainly studies the methods of UAV detection and motion parameter estimation with STLFMCW radar.

Usually, the echo of the moving target of interest is corrupted by those of varying clutter or other unexpected interference targets, i.e. the target of interest exists in non-homogeneous clutter, which increases the detection threshold and deteriorates the detection performance. Therefore, it is of great significance to study CFAR detector [2] in the non-homogeneous clutter environment. Usually, the clutter is modelled with Weibull distribution [3] as also used in this paper.

Recently, the researchers have developed a series of radar target detection methods based on the echoes in pulse compression domain. Xu et al. [4, 5] first presented Radon–Fourier transform (RFT) to realise the long-time coherent integration with MTRC compensation for uniform motion. To deal with the high-order motion of the target, an extended version named by generalised RFT (GRFT) is also provided. For the purpose of fast implementation, Yu et al. [6] proposed a sub-band frequency RFT detector, which can significantly reduce the memory requirement with an acceptable performance loss. As a non-searching algorithm, the adjacent cross-correlation function (ACCF)-based method [7] has close estimation performance and less computational cost compared with GRFT. Aiming at the manoeuvring targets detection in clutter environment, Radon-fractional ambiguity function (RFRAF) [8] and Radon-fractional Fourier transform (RFRFT) [9] are proposed to improve the detection probability. To reduce the dimension of searched parameters, the time reversing transform (TRT) [10] is applied which can remove odd-order range migration. Furthermore, the range curvature is removed by using second-order keystone transform (SKT) [10, 11]. In response to the impact of complex clutter, this paper mainly studies the methods of UA VLFMCW radar transmits continuous waveform with sawtooth radar, a SK-CFAR detector is proposed based on the local spectrum refinement. By using zoom-FFT, the two-dimensional spectrum of the received signal is extracted for local template matching. Subsequently, the two-dimensional SK-CFAR detector and CLEAN technique are applied to decide whether there exist some targets in the region of interest. Compared with Radon–Fourier transform (RFT) to realise the long-time coherent integration with MTRC and moving target detection (MTD), the proposed estimator based on local speed compensation is a good choice for the trade-off of high performance and low computational load even though the input signal-to-clutter ratio approaches to ~24 dB.

2 Signal model
Assuming that the radar transmits STLFMCW signal which is described as follows:

\[
s(t, \tilde{t}) = \text{Arccstt} \left( \frac{i + \frac{\mu}{2} \tau^2}{T} \right) \exp \left( j2\pi \left[ \frac{f_A}{T} \right] \right)
\]

(1)

\[
s(t, \tilde{t}) = \text{Arccstt} \left( \frac{i - T - f_m}{T} \right) \exp \left( j2\pi \left[ \frac{f_A}{T} \right] \right)
\]

(2)

where \( t \) is the total time, \( t_m = mT \), is the slow time at which the \( m \)-th pulse is transmitted, \( M \) is the number of accumulated cycles, \( t = t - t_m \) is the fast time. \( A \) is the signal amplitude, \( f_s \) is the carrier frequency, \( T \) is the modulation period, \( T_r = 2T \) is the sweep period of the transmitted signal, \( f_{s_1} = 1/T_r \) is the pulse repetition frequency (PRF). \( \mu \) is the chirp rate, and \( B = \mu T \) is the signal bandwidth.

Neglecting the additional phase shift caused by the target reflection, the echo signal is expressed as follows:

\[
s(t) = K_r \times s(t - t(t))
\]

(3)

where \( K_r \) is the target reflection coefficient, \( t(t) \) is the time delay of the target at the moment \( t \). For uniformly moving target with radial velocity \( v \), \( t(t) = t_0 + k t \), where \( k = 2v/c \) and \( t_0 \) are the initial distance between the target and the radar at \( t = 0 \).

After the echo being dechirped with the transmitted signal, it satisfies

\[
s_d(t, \tilde{t}) \approx A_0 \text{Arccstt} \left( \frac{i - f_{\text{chirp}}}{f_s} \right) \exp \left( j2\pi \left[ \frac{\mu}{2f_{\text{chirp}}} \right] \right)
\]

(4)

\[
s_d(t, \tilde{t}) \approx A_0 \text{Arccstt} \left( \frac{i - f_{\text{chirp}}}{f_s} \right) \exp \left( j2\pi \left[ \frac{\mu}{2f_{\text{chirp}}} \right] \right)
\]

(5)

where \( A_0 = K_r A^2 \), \( f_{\text{chirp}} = f_d + \mu \nu + \nu k t_m \), \( f_{\text{chirp}} = f_d - \nu \mu - \mu k t_m \), \( \nu = f_r + \tau_0 - (\mu/2) \tau_0 \), \( \nu = 2B \tau_0 + f_r + \mu/2 \tau_0 \).

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3 SK-CFAR detector based on the local spectrum refinement

In order to obtain the parameter of a moving target, the two-dimensional frequency domain of a signal can be directly searched by the maximum-likelihood estimation (MLE). However, this method has a large amount of calculations. Since the spread of the target spectrum is usually much smaller than that of the noise spectrum, the most resource of the global compensation are consumed in the calculation of the noise spectrum. Therefore, a local compensation method that only analyses the frequency region near the target spectrum can be adopted, which effectively reduces the amount of operations in search process.

3.1 Local template matching

Taking two-dimensional FFT on (4), one can get the signal frequency spectrum \(S_y(m, n)\). Denoting \((f_{p1}, f_{p2}) = \arg\max_{m,n} \ S_y(m, n)\), the ambiguous Doppler frequency \(f_{amb}\) and range frequency \(f_{b}\) can be written as follows:

\[
\begin{align*}
  f_{amb} &= \frac{f_{p1}}{M f_{s1}} \\
  f_{b} &= \frac{f_{p2}}{N f_{s2}}
\end{align*}
\]

(6)

Due to the target motion speed, the target motion will be spread into a region centred at \((f_{p1}, f_{p2})\), which is named by the region of interest (ROI). The central \(v_{max}\) as the maximum velocity of the target, the size of the ROI is selected as \(J \times J\) such that \(J \geq 2\sigma m\mu_{mt}MT^2\), where \(\mu_{mt} = 2v_{max}/c\). Generally, \(J\) is the power of 2.

Since zoom-FFT [13] is a perfect method for local spectrum analysis, it is used to analyse the spectrum \(S_y(m, n)\), extract the ROIs, and decide whether there exist some targets in them.

Denoting the shifted spectrum as \(G_j(j_i, j_o)\), i.e.

\[
G_j(j_i, j_o) = S_y(j_i + m_J, j_o + m_N)
\]

(7)

where \(m_J = f_{p1} - J/2 + 1\) and \(m_N = f_{p2} - J/2 + 1\), one can obtain the corresponding time domain signal \(g_j(m, n)\) which includes the target motion information by taking IFFT on (7). It is known from [13] that \(g_j(m, n)\) is equivalent to the descimated signal from \(S_y(m, n)\) with the zooming factors \(K_J = M/J\) and \(K_N = N/J\) in velocity and range domain, respectively. Therefore, the local speed template can be written as

\[
x_p(m, n) = \exp\left(-\frac{2\pi y_{amb}^2}{J^2 f_s K_J f_{s1}} \right)
\]

(8)

where the compensation channel number is \(P = \text{ceil}(2v_{amb}/c) + 1\), \(y_{amb}\) is the searching step in velocity domain, \(y_{amb} = 2v_{max}/c\), \(y_{amb} = -v_{max} + (p-1)v_{amb}\).

Using the above local speed template to compensate \(g_j(m, n)\), the compensated signal is given as follows:

\[
x_0(m, n) = g_j(m, n) \times x_p(m, n)
\]

(9)

Let \(Z(p) = \max(m,n) \cdot \text{FFT}_{m,n}(\zeta_p(m, n))\) and \(p_0 = \max, Z(p)\), where \(\text{FFT}_{m,n}(\zeta_p(m, n))\) is the two-dimensional FFT of \(\zeta_p(m, n)\) with respect to \(m\) and \(n\), one can obtain the rough estimate of the target velocity \(\hat{y} = -v_{max} + (p_0 - 1)v_{amb}\) and the corresponding range frequency \(\hat{y} = f_{amb}(p_0)\).

Subsequently, the down sweeping echo \(g_j(m, n)\) is compensated by using the constructed signal given as follows:

\[
x_0(m, n) = \exp\left(-\frac{2\pi y_{amb}^2}{J^2 f_s K_J f_{s1}} \right)
\]

\[
  m = 0, 1, \ldots, J - 1 \quad n = 0, 1, \ldots, J - 1 \quad p = 1, 2, \ldots, P
\]

(10)

where \(k = 2v_{amb}/c\). Taking two-dimensional FFT on the compensated signal and searching for the maximum peak in the frequency domain, we can get the range frequency \(f_{amb}(p_0)\) of the down-chirp signal. It will be used for the discrimination of the ROI.

3.2 Target discrimination

We know that the skewness [14] denoted as a measure of the distribution deflection. Using a logarithmic amplifier to convert the random variable with Weibull distribution into another one with Gumbel distribution [3], the skewness does not change with the value of the clutter parameter [15]. Therefore, we study a SK-CFAR detector that combining skewness with Log-t CFAR detector [16]. The workflow of the SK-CFAR detector is shown in Fig. 1.

As shown in Fig. 1, set the sliding window area with a side length of \(L = 33\), centre \(D\) is the detected unit, and the remaining units constitute the reference window. The signal output through the two-dimensional FFT is amplified by a logarithmic amplifier with the reference window sequence \(Y_1, \ldots, Y_{16,15}, Y_{16,17}, \ldots, Y_{L,L}\).

The sorted reference window sequence is denoted as \(Y_{1,L}, \ldots, Y_{1,15}, Y_{1,16}, \ldots, Y_{L,L}\), where \(Y_{L,L}\) has the largest amplitude. The skewness SK is calculated as

\[
SK = \frac{\sum_{l=1}^{L} (Y_{l,l} - \mu)^3}{(L - 1)\sigma^3}
\]

(11)

where \(\mu = (1/(L^2 - 1)) \sum_{l=1}^{L} Y_{l,l} \approx (1/(L^2 - 1)) \sum_{l=1}^{L} (Y_{l,l} - \mu)^3\).

To decide whether there exist unexpected targets in the reference window, set a threshold \(T_{SK}\) of skewness detector which satisfies

\[
P_{fa} = P(SK > T_{SK})_{\text{homogeneous clutter}}
\]

(12)

where \(P_{fa} = 10^{-3}\) is the false alarm rate. Since, it is difficult to derive the statistical characteristics of the skewness threshold \(T_{SK}\) in non-homogeneous clutter, Monte-Carlo experiments are done according to (12). Simulation results are shown in Table 1.

One can delete the unexpected targets corresponding to \(Y_{1,L-1+1}, \ldots, Y_{1,2}\). In the reference window, then compute the skewness in (11) and compare SK with \(T_{SK}\) again.

According to the SK-CFAR detector, a target of interest can be discriminated. Then, one can estimate the initial range and accurate speed by decoupling \(f_{amb}(p_0)\) and use the CLEAN technique.
subsequently to solve the motion parameter estimation of other targets in turn. This algorithm is named by a SK-CFAR detector based on the local spectrum refinement, and the overall flow chart is shown in Fig. 2.

It can be seen that the computational load of the proposed algorithm mainly comes from the FFT operations for the ROIs. For comparison, the computational loads of the proposed algorithm, the direct MTD and RFT method in [4] are listed in Table 2.

### Table 1: TSK for delete different number of units

| No. of units i | 0 | 1 | 2 | 3 |
|----------------|---|---|---|---|
| TSK(i)         | 1.265 | 1.37 | 1.475 | 1.58 |

The zero memory non-linear transformation method (ZMNL) [17] is used to simulate Weibull clutter with the shape parameter $p = 1.452$ and the scale parameter $q = 1.612$, the clutter variance is 1.

In order to analyse the performance of the proposed method, we provide detailed comparisons from three aspects, i.e. coherent integration ability, detection performance, and computational burden, respectively.

### 4.1 Coherent integration ability

Fig. 3 shows the integration results of the local template matching compared with those of the MTD and RFT methods. It is shown that the integrated result of MTD does not focus in a single range-Doppler cell while the other two methods do. In addition, the peak value of MTD is much smaller than the other two, while the RFT method and the proposed method exhibit the similar performance of signal accumulation.

To further illustrate the coherent integration ability of the RFT (—) and the proposed method (—), Fig. 4 gives the root-mean-square error (RMSE) of the initial range of these two algorithms.

### Fig. 2: Algorithm flow chart

### Table 2: Computational complexity of three methods

| Methods     | Computational complexity                                      |
|-------------|----------------------------------------------------------------|
| MTD         | $10NM \log_2 N + 9NM + 5NM \log_2 M$                           |
| RFT         | $10NM \log_2 N + 33MN + 20MN \log_2 (2M)$                      |
| proposed method | $2P^J \log_2 J + MN \log_2 (MN)$                           |

### Table 3: Radar simulation parameters

| Parameters          | Values | Parameters          | Values |
|---------------------|--------|---------------------|--------|
| carrier frequency $f_c$ | 20 GHz | sweeping period $T_r$ | 2 ms   |
| bandwidth $B$       | 100 MHz| pulse number $M$     | 256    |

### Table 4: Targets simulation parameters

| Parameters          | Target 1 | Target 2 | Target 3 |
|---------------------|----------|----------|----------|
| initial range $r_0$ (m) | 1005     | 1010     | 1100     |
| speed $v$ (m/s)     | 15       | 15       | 20       |

The parameters about the radar and the targets in the simulations are listed in Tables 3 and 4, respectively.
methods in a certain input SCR range. It is clear from Fig. 4b that both of them have high estimate accuracy, and their RMSE is very close.

4.2 Detection performance analysis

To evaluate the abilities of these three detectors in non-homogeneous clutter, the detection performance curves of the MTD (‘- - - ’), RFT (‘ ‘), and the proposed method (‘ - - - ’) are illustrated in Fig. 5. In the simulation, the false alarm rate is given as $P_{fa} = 10^{-3}$, and there is one interference target in the scenario. Fig. 5 shows that the detection performance of the proposed method is highly superior to that of the MTD method and worse than the RFT method. When $P_d = 0.9$, the required SCR for the proposed method is improved by 17 dB than that of the MTD, while degrades by about 9 dB than that of the RFT method.

4.3 Computational complexity

To demonstrate the computational complexity presented in Table 2, the computational amounts are illustrated in Fig. 6, where the number of pulse are set as $M = 16, 32, 64, 128, 256, 512, 1024$, respectively. It is obvious that the RFT method (‘ ‘) has the largest computational amount than other two methods. For $M = 256$, the computation amount of the proposed method (‘ - - - ’) is about 0.09 of the RFT method. Although the calculation of the MTD method (‘- - - ’) is less than that of the RFT, it is ineffective in coherent integration. Therefore, the proposed method can achieve a good balance between the integration ability and computational cost even though the input SCR reaches to $-24$ dB.

5 Conclusion

In this paper, a local spectrum refinement-based SK-CFAR detector is proposed to detect UAV in non-homogeneous clutter and estimate its motion parameter. By only matching template in the extracted ROIs, the amount of computation is reduced while obtaining better parameter estimation accuracy. The real targets are discriminated accurately by SK-CFAR detector as well. Experimental results demonstrate the superiority of the proposed method in terms of calculation and integration ability provided that the input SCR reaches to $-24$ dB.

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