Signal Detection in Multi-Frequency Forward Scatter Radar

M. Gashinova[*1], V. Sizov[#2], N.A.Zakaria[*3], M. Cherniakov[*4]

[*]*School of Electronic, Electrical and Computer Engineering*
University of Birmingham
Birmingham, United Kingdom
[1]gashinms@bham.ac.uk
[4]cherniam@bham.ac.uk
[#]*Department of Radio-Electronics*
Moscow Institute of Electronic Technology
Moscow, Russian Federation
[2]sizov_vi@rambler.ru

***Abstract* — The peculiarity of Forward Scatter Radar (FSR) is the absence of range resolution. As a consequence, possible low signal-to-clutter ratio is the most limiting factor in FSR detection. In this paper we will discuss non-coherent and coherent FSR Doppler signal processing and consider an alternative cross-correlation approach, which could be called 'quasi-coherent' processing. Multi-frequency radar enables correlation of Doppler output of one of the channels with another which can be considered as the matching waveform, or the reference signal, to the first signal. This leads to a compression of the FSR return by cross-correlation with enhanced processing gain, and, consequently, enhanced detection.**

I. Introduction

Two traditional approaches are used in radar for automatic targets detection (ATD). These are the coherent signal processing (CSP) and the non-coherent (post-detector) signal processing (NCSP). If radar is fundamentally coherent, the CSP is the optimal processing that provides a maximum signal-to-noise ratio (SNR) at least in the case of Gaussian noise. For the CSP, the reference signal (i.e. the copy of the transmitting signal) must be known and compared with the received signal. NCSP is usually technically simpler and rather effective in terms of ATD if the signal dominates above the noise. However, the efficiency of NCSP dramatically reduces as soon as SNR becomes less than 0 dB. In this paper we propose a new approach for signal detection in FSR. This approach will provide signal compression which is no more than 3dB worse than in CSP for any SNR, and is technically achievable. The method is based on cross-correlation of signals from two coherent frequency separated channels. The description and justification of this method is the subject of this paper.

The concept of a forward scatter micro-sensors radar network for situational awareness in ground operations was described in [1]. The network consists of a number of nodes (separated short-range transmitter/receiver pairs) operating in forward scatter configuration with a continuous wave and intended for detection and recognition of moving ground targets such as personnel and cars intruding the protected area.

Vegetation may surround radar position and be presented in close proximity to Tx/Rx and directly on the baseline. Fundamentally, FSR does not have the range resolution, and clutter is picked up from a large volume where spatially distributed clutter sources may form backscattering, bistatic and forward scattering signal interference. As a result, the clutter component may entirely mask the target component in FSR return in the time domain and we can expect poor performance of non-coherent detection. In this case coherent detection is expected to give conclusive results.

The essence of coherent detection is signal compression due to matching filtering of radar return when the acquired signal correlates with a reference waveform. In contrast to conventional radar, where the reference function is the delayed and frequency-shifted transmitted waveform, the received signal in FSR depends on the target's speed, RCS and trajectory and is a priori unknown. Thus, the optimal filtering process represents the problem of sequential correlation of the received signal with a set of pre-defined reference waveforms. Maximisation of correlation is a criterion for a particular reference function to be a matching waveform. Hence coherent detection is accompanied by target trajectory and speed estimation.

Despite its advantages, coherent detection processing for FSR is both time and resource consuming. We can expect to require thousands of reference functions to cover all the possible trajectories and velocities of targets within a 3 dB loss criterion of the compressed signal gain.

Use of multi-channel equipment, however, enables a 'lite' version of coherent processing, where FSR returns from one channel is used as a reference function to the other. Returns may consist of either a composition of signal and clutter/noise or just clutter and, again,, clutter power may exceed the target power. However, if we assume that clutter signals at different channels are de-correlated while target signatures are correlated after re-sampling, we can expect compression gain in the presence of a target and, therefore, detection in the background of low-correlated clutter.

The aim of this paper is to analyse the correlation properties of clutter and Doppler target signatures and to introduce cross-correlation algorithms.

We will start with a model of vegetation clutter, repeating the basic assumptions presented in [2] in order to maintain the integrity of the description. We will then proceed with cross-channel correlation processing for measured clutter signals and target signatures. Finally we will consider the CFAR automatic detection procedure for cross-correlation processing when sections of the input signals at two frequencies are convolved within the same relatively short sliding window for background estimation and detection.

II. Cross-correlation

In radar application, cross-correlation is a measure of similarity between two signals. The higher the cross-correlation coefficient, the more similar the two signals are.

Radar signal processing typically deals with the finite sampled waveform, which we will consider as a section of the statistical process. In multi-channel applications we will consider a sampled version of two signals of the same length N $\{x_n\}\big|_{n=0}^{N-1}$ and $\{y_n\}\big|_{n=0}^{N-1}$ with coefficient correlation between them

$$\hat{r}_{x,y} = \frac{\sum_{n=0}^{N-1}\left(x_n - \hat{m}_x\right)\left(y_n - \hat{m}_y\right)}{N\hat{\sigma}_x\hat{\sigma}_y}, \qquad (1)$$

and $\hat{m}_x$, $\hat{m}_y$ are the mean values and $\hat{\sigma}_x$, $\hat{\sigma}_y$ are the rms of the signals. We must point out here that the longer the sampled signals with larger deviations from the mean levels, the smaller the cross-correlation coefficient.

Let us suppose that at the output of a two-channel receiver we have two Doppler signals corresponding to two carrier frequencies of the transmitted signal f_1, f_2, with sampling rate f_s acquired coherently during time T_s.

There are three general situations which can arise: (1) if the signals are similar waveforms but have a different 'time scale' or spectra (Doppler signatures of target) after proper re-sampling, we can expect the correlation coefficient between them to increase compared with a correlation of signals that have not been re-sampled; (2) if the signals are similar and have the same 'time scale' or spectra (correlated clutter), we can expect a decrease of the correlation coefficient, (3) in the case of fully dissimilar signals (independent noise-like signals), the originally low correlation coefficient should not change significantly after re-sampling.

A. Target signals

Target signature represents a chirp-like signal which in direct-path approximation can be presented as:

$$S_r\left(t,\omega\right) = A\left(t\right)\sin\left[\omega\cdot\frac{T_T(t)+R_T(t)}{c}\right] \qquad (2)$$

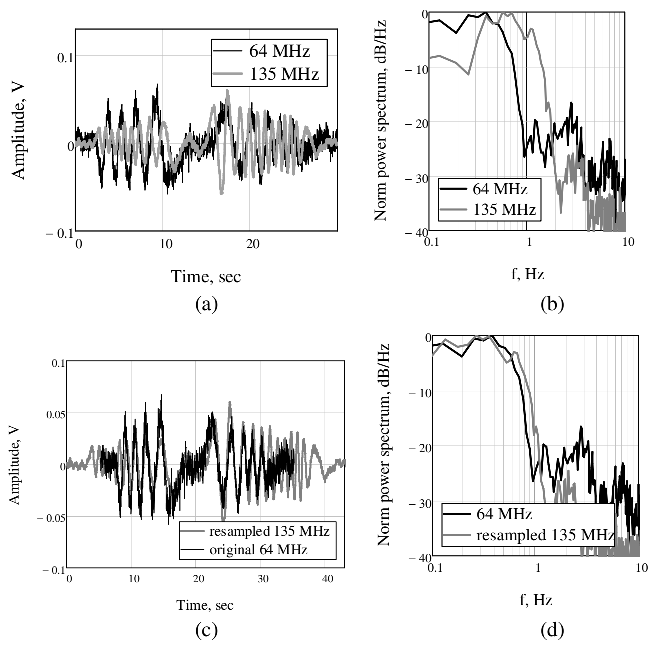

Fig. 1 FSR Doppler signature of human target moving perpendicularly to the baseline (100 m) in the middle with a speed of 6 km/h (a) receiver output signals at 64 MHz and 135 MHz channels, (b) normalised PSD, (c) signal waveforms after re-sampling, (d) normalised PSD after re-sampling

where $A(t)$ is the envelope of the received signal (proportional to propagation loss and RCS of a target), ω is the carrier angular frequency of the transmitted signal, T_T, R_T are the variable ranges from Tx and Rx to the moving target, c is the velocity of light in free space. The signature of the same target at the output of two channels is given by pair $S_r(t,\omega_1)$ and $S_r(t,\omega_2)$ where the signal at a higher frequency may be considered as the compressed version of the signal at a lower frequency (Fig 1 (a)) in the time domain and, in the frequency domain, as the signal with a larger Doppler frequency bandwidth (Fig. 1 (b)).

We found that the re-sampling factor for the higher frequency signal is proportional to $\sqrt{f_2/f_1}$ and after re-sampling both signals have the same "time scale" and bandwidth, although

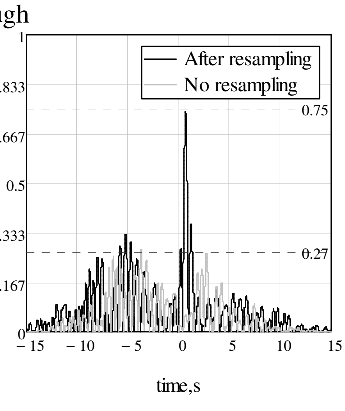

Fig. 2 Signal compression when two signals from 64MHz and 135MHz channels are correlated with each other before and after re-sampling.

they have different lengths and total times (Fig. 1 (c), (d)). Correlation result is shown in Fig. 2. The comparison of cross-correlations for re-sampled and original signals demonstrates significant compressed signal gain after re-sampling; 2.8 times higher than the correlation of original signals.

B. Clutter signals

In our previous paper [2] we demonstrated that the specifics of clutter can be understood if clutter from vegetation is modelled as a return from a set of independent pendulums oscillating within π-separated isophase contours of a Doppler phase plane. The modelling of clutter is described in detail in [2] and simulated clutter signals at three operating frequencies as well as their PSD are presented in Fig. 4.

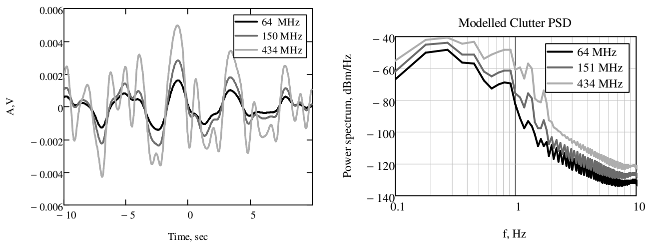

Fig. 3 (a) signals modelled as a return from a set of 30 pendulums, (b) PSD.

In order to confirm theoretically predicted clutter characteristics an extensive campaign of clutter measurements was undertaken, where clutter signals were recorded at different test sites with terrain profiles varying from a concrete runway to dense woods. In particular it was found that for the vast majority of records in different environmental conditions clutter demonstrated certain invariance of PSD.

An example of PSD of returns at four frequency channels is shown in Fig. 4. Being recorded during the day with light-to-medium wind it, nevertheless, reflects the most typical situation. Total clutter power increases in about the fourth power of the carrier frequency with a difference of 18 dB between 135 MHz and 434 MHz channels. At the lowest frequency (64 MHz), clutter power becomes low and the signal is defined by receiver thermal noise (noticeable when there is no wind) with a probability density function close to Rayleigh and reflects therefore in general the Gaussian nature of clutter at a low frequency. However, as the wind rises, low frequency clutter became Non-Gaussian. For higher frequencies clutter is always defined by wind blown vegetation and becomes Weibull distributed and partly-correlated. The spectrum width (0.4-0.5Hz) is practically invariant of the carrier frequency.

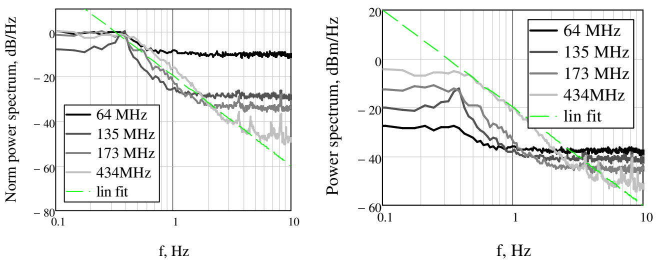

Fig. 4 Power spectrum density of measured clutter (left – normalised to maximum, right – absolute values)

Keeping in mind the procedure of automatic detection where background estimation is performed within a short window, we will take a look at short sections of clutter (Fig.5) .

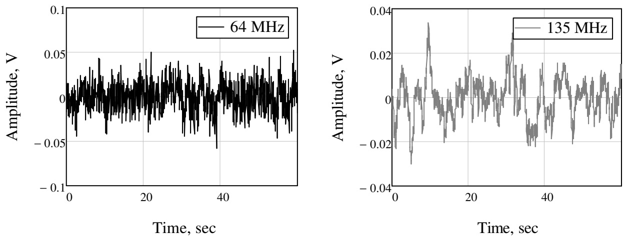

Fig. 5 Short sections of clutter.

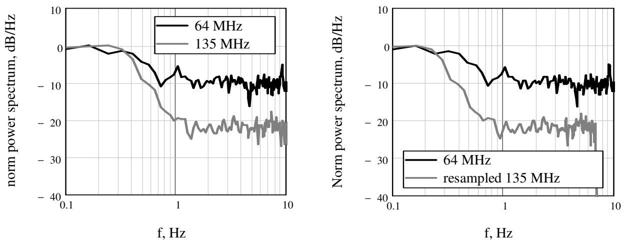

Fig. 6 PSD of signals in Fig. 6.

Spectra of the original signals and their re-sampled versions are presented in Fig. 6. There is some difference between the two signals and re-sampling with following correlation leads to decrease of cross-correlation product (Fig.7 (a)). We must stress here that the relatively high correlation coefficient in Fig. 7 (a) is a result of an operation with two truncated short signals, while for longer correlated clutter signals the correlation decreases with the length of the signals (Fig. 7 (b)).

The correlation coefficient trend before and after re-sampling for clutter records made at twelve different testing sites for low and moderate wind speed is shown in Fig. 8. In most cases, re-sampling leads to a decrease of the correlation coefficient which indicates some degree of correlation of the original clutter records.

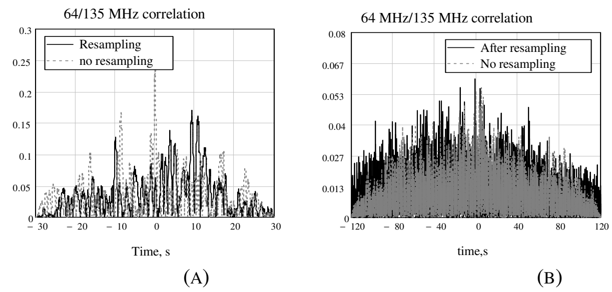

Figure 7. Compressed signals with and without re-sampling. (a) Cross-correlation product of 1 min sections corresponding to Fig. 6; (b) – cross correlation of extended 4 mins signals

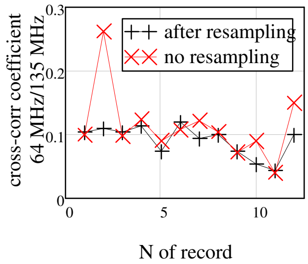

Fig. 8. Correlation coefficients over twelve records made at different sites.

Having so far considered correlation properties of short sections of clutter or target signals after re-sampling, we now continue with the use of cross-channel correlation processing for automatic detection.

III. CFAR DETECTION BY QUASI COHERENT DETECTION

In the introduction we noted the use of non-coherent and coherent detection for FSR scenarios. As an alternative processing method the described cross-correlation procedure can give reasonable performance yet be less computationally extensive than coherent processing and more robust to SCR than non-coherent integration. Additional benefits include detection of targets moving by complex trajectories where coherent detection may fail.

The algorithm used for detection is a cell-averaging CFAR. The Doppler signature length of the smallest and lowest target defines the length of the sliding window or detection cell. A human target signature at the lowest operating frequency of 64 MHz lasts nearly 35 seconds when a human is crossing the baseline perpendicularly in the middle with a speed of 6 km/h.

Within each window sections of, coherently acquired signals at two different frequencies are filtered and integrated over 1.25s with following correlation after re-sampling. We used a one-sided range interval supporting the background estimator by three-to-six cells overlapping by ¼ of their size. An adaptive threshold is built to meet $P_{FA}<10^{-3}$. Detection is triggered when a maximum of correlation product exceeds the threshold.

Fig. 9 depicts the detection of three targets with differing echo strengths. Target T2 is missing in non-coherent detection and is detected by cross-correlation detection.

IV. CONCLUSIONS

In this paper we have discussed the method of signal processing for ATD in FSR based on signal correlation in two frequency separated channels. In contrast to known approaches, which have been used in foliage penetrating radar with frequency separation by an octave in order to de-correlate clutter, only a 30% shift between the frequencies is needed in the proposed approach. ATD using cross-correlation in presence of strong non-stationary clutter from vegetation demonstrated a better performance in comparison with NSP and is less computationally

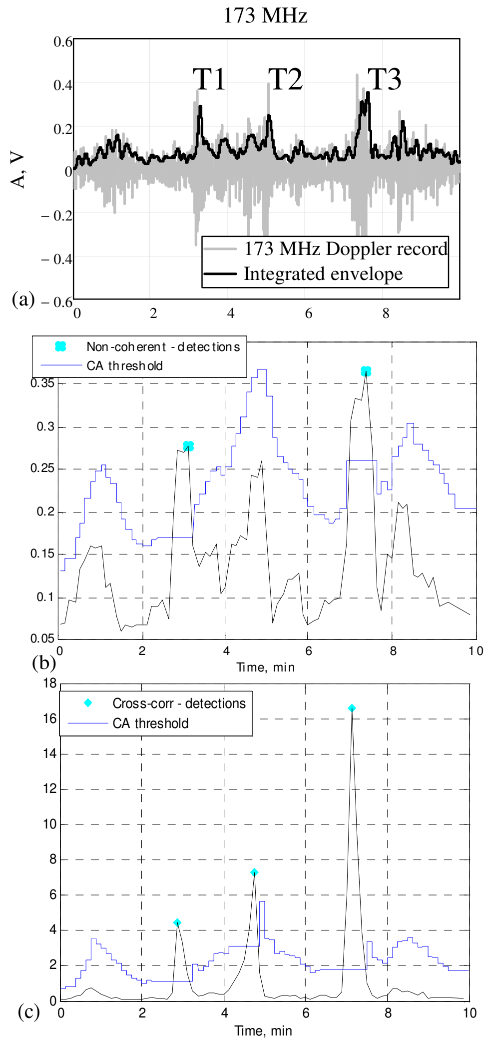

Fig. 9 Target detection : (a) record consisting of three target echoes; (b) non-coherent processing (b) cross-correlation processing.

demanding than CSP. This paper is the first publication on the topic. In subsequent publications we are planning to discuss the problem of optimisation of FSR and the use of a CFAR algorithm for high cross-correlation processing performance.

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