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Iterative Adaptive Approach for Unambiguous Wideband Radar Target Detection

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***Abstract*—In this paper the problem of unambiguous target detection with wideband radar is discussed. A range migration phenomenon is used to resolve Doppler ambiguities present in low pulse repetition frequency mode. Iterative Adaptive Approach is applied to solve this problem and shown to be an attractive solution. Capability of the proposed processing is shown via numerical simulations. Experimental data sets demonstrate 25 dB improvement in detection performance of a moving target at the first blind velocity.**

Keywords—Iterative adaptive approach (IAA); wideband radar; target detection; range migration; velocity ambiguity.

I. INTRODUCTION

Moving target detection in presence of clutter is usually performed by Doppler processing. However, this technique has some limitations coming from the relation between the ambiguous velocity v_a and the ambiguous range R_a.

To overcome this issue staggered PRF waveforms are usually used. Limited time-on-target duration and as a consequence shorter coherent processing interval (CPI) for each PRF are obvious limitations of this approach [1].

Recently wideband (WB) radars have attracted significant attention due to their advantages for target detection and classification due to high range resolution (HRR). However, detection of moving targets with WB radar faces new phenomena coming from fact that fast moving targets migrate from one resolution cell to another during the CPI [1]. This phenomena leads to a peak loss in Doppler processing output and has to be compensated. On the other hand, if low PRF mode is used, it becomes possible to take advantage of this range walk to mitigate velocity ambiguities. Correct estimation of target migration and thus unambiguous velocity can be done via a high spectrum resolution achieved in this paper with Iterative Adaptive Approach (IAA).

This paper is organized as follows. In section II, the signal model for WB radar is introduced. Also some existing methods are discussed, and the choice of IAA to deal with this problem is emphasized. In section III, IAA is revisited for WB moving target indication (MTI). Numerical results are shown in section IV. Application for PARSAX experimental data is presented in sections V. Finally, conclusions are drawn in section VI.

II. WIDEBAND DATA MODEL

Herein we consider a pulse-Dopper radar with wideband waveform. The radar sends a series of M pulses with PRF $f_r = 1/T_r$ where T_r is the pulse repetition interval (PRI). By wideband we mean that the bandwidth B spans 5-25% of the carrier frequency $f_c = c/\lambda_c$. A low PRF is considered so that no range ambiguities occur but the maximal Doppler frequency is aliased around ambiguous velocity $V_a = \lambda_c/(2T_r)$, and $V_{max} > V_a$ where V_{max} represents the maximum target velocity expected for a target. Furthermore, the range migration of a scatterer at the ambiguous velocity is assumed to be negligible within one PRI: $V_a T_r << \delta_R$, but significant over the whole CPI: $V_a M T_r > \delta_R$, where $\delta_R = c/(2B)$ is the range resolution.

A. Data model

Usually with narrowband radar, detection is performed range gate by range gate. However, in case of a wideband waveform, moving targets migrate so detection should be performed after range compression on a block of K adjacent range cells called low range resolution (LRR) segment [1]. Samples to be processed can thus be represented by a $K\times M$ matrix where the first and second dimensions refer, respectively, to the fast- and slow-time. However, the data model can be more conveniently expressed after applying fast Fourier transform (FFT) on the fast-time - in the fast-frequency/slow-time domain. Taking into account HRR of the radar, both clutter and targets can be modelled as multiple scatterers. Then $K\times M$ data matrix can finally be expressed as:

$$\boldsymbol{Y} = \sum_{n=1}^{N} x_n \boldsymbol{A}_n + \boldsymbol{N}\,, \tag{1}$$

where N, x_n, represent, respectively, the number of scatterers and the n-th complex amplitude, $\boldsymbol{A_n}$ is a $K\times M$ matrix containing target signature and $\boldsymbol{N}$ is the receiver noise. The receiver noise is assumed to be bi-dimensional spectrally white Gaussian random process with power σ^2.

The scatterer signature $\boldsymbol{A}$ involved in (1) has been studied earlier [2, 3] and was shown to be the product of a two-dimensional (2D) cisoid with cross-coupling terms. More precisely, the (k, m)-th element (where $m = 0...M-1$, $k = 0...K-1$) of the matrix $\boldsymbol{A}$ can be expressed by:

$$A_{k,m}(\tau,V)=\exp\left(j2\pi\left(-\tau\frac{B}{K}k+\frac{2Vf_c}{c}T_r m+\frac{2V}{c}\frac{B}{K}T_r km\right)\right), \quad (2)$$

where τ and V designates the initial round-trip delay (range) and velocity of the scatterer respectively. The first two terms in (2) represent a fast-time (range) frequency $-\tau$ sampled at a rate B/K and a Doppler frequency $2Vf_c/c$ associated with slow time sampling T_r. The third component is cross-coupling term specific for the wideband waveform. It corresponds to range migration of the target and depends only on its radial velocity V. Moreover, measuring velocity via range migration is unambiguous contrary to Doppler frequency measurement.

Equation (2) can be rewritten as:

$$A_{k,m}(\tau,V)=\exp\left(j2\pi\left(-\tau\frac{B}{K}k+\frac{2Vf_c}{c}T_r m\left(1+\frac{B}{Kf_c}k\right)\right)\right). \quad (3)$$

In (3) the second term represents Doppler frequency at the k-th subband. On the contrary it can be interpreted as a Doppler shift at carrier frequency f_c but with PRI depending on the fast-frequency index as: $T_r' = T_r(1+Bk/(Kf_c))$ [3]. Consequently, the signal of interest $\boldsymbol{A}$ is a bi-dimensional cisoid with constant sampling rate over fast frequency and sampling rate in slow time varying linearly from one subband to another.

The number of targets in the scene N is usually unknown, but it can be substituted by the number of all possible range cells in the LRR segment and all velocity cells of the interests limited by $|V|<V_{max}$, i.e. $N = N_tN_v$ $(t = 0...N_t-1,\ v = 0...N_v-1$ – indexes in range-velocity grid). Then complex amplitudes of range-velocity map of interest are the elements of matrix $\boldsymbol{X}$ of size $N_t \times N_v$:

$$\boldsymbol{Y}=\sum_{t=1}^{N_t}\sum_{v=1}^{N_v}\boldsymbol{X}_{t,v}\boldsymbol{A}(t,v)+\boldsymbol{N}\ , \quad (4)$$

where the target at indexes t and v have scatterer signature $\boldsymbol{A}(t,v)$ with time delay $\tau = t\delta_R/(ck_t)$ and velocity $V=v\delta_V/k_v$, where $\delta_V = V_a/P$, and k_t, k_v are oversampling factors in range and velocity respectively.

An equivalent vector notation can be used for (4):

$$\boldsymbol{y}=\sum_{t=1}^{N_t}\sum_{v=1}^{N_v}\boldsymbol{X}_{t,v}\boldsymbol{a}(t,v)+\boldsymbol{n}\ , \quad (5)$$

where $\boldsymbol{y}$, $\boldsymbol{a}(t,v)$ and $\boldsymbol{n}$ are KM-length vectors obtained by row-vectorization of corresponding matrices and $\boldsymbol{X}_{t,v}$ – is the complex amplitude of the scatterer at range cell t and velocity cell v. Taking into account that the number of possible range and velocity hypothesis are known, the previous equation can be represented in matrix notation as:

$$\boldsymbol{y}=\boldsymbol{H}\boldsymbol{x}+\boldsymbol{n}\ , \quad (7)$$

where the matrix $\boldsymbol{H}$ is $KM \times N_tN_v$ matrix of all possible scatterer signatures $\boldsymbol{A}(t,v)$ in vectorised form, i.e. $\boldsymbol{H} = [\boldsymbol{a}(1), ..., \boldsymbol{a}(i), ..., \boldsymbol{a}(N_tN_v)]$ and $i = t + N_t(v-1)$. Vector $\boldsymbol{x}$ is the row-vectorised matrix $\boldsymbol{X}$, which is of interest. Note that matrix $\boldsymbol{H}$ in the case of unambiguous detection has less rows than columns $KM < N_tN_v$.

B. Related work

Have migration effect introduced, Fourier-like technique taking into account the variation of Doppler frequency over the band was proposed and called wideband coherent integration (CI) [1]. It allows the gain on the target peak to be preserved and can be done in matrix notation by:

$$\boldsymbol{x}^{CI}=\boldsymbol{H}^{\boldsymbol{H}}\boldsymbol{y}\ , \quad (7)$$

where $()^H$ stands for Hermitian transpose. Although efficient this processing still keeps strong residuals at aliased velocities (called ambiguous sidelobes) limiting its ability to extract moving targets unambiguously.

Advanced methods to deal with wideband signal model can be classified as methods coming from adaptive spectrum estimation and ones coming from compressive sensing (CS).

The problem is shown in (7) as an undetermined system of equations. CS is a modern approach to solve this kind of problem exploiting sparsity. Moreover non-uniform sampling is natural for sparse algorithms. Limitations of these techniques come from the clutter, which is typically non-sparse. A Bayesian approach exploiting sparsity with application for unambiguous target detection was studied in [3] and shows impressive results, albeit with a high computationally price. The extension of this approach to deal with ground clutter is proposed in [4] taking into account an autoregressive model of ground clutter.

Enhanced spectral estimation techniques, named W-Capon, W-APES and CLEAN-like algorithm named IW-Capon have been proposed in [2] and show better ability to suppress ambiguous sidelobes of clutter than CI. Performance limitations come from the invalid estimation of the noise plus interference covariance matrix (migration effect limits the possibility of averaging, required for covariance matrix estimation). However, the simulation for the clairvoyant case (known covariance matrix) shows impressive result with much better ability than CI to suppress ambiguities [2]. Unfortunately, it cannot be implemented in real operation.

Previous arguments show that the problem can be solved with spectrum estimation method having following features:

- Robust with respect to non-uniform sampling;
- No strong limitation on sparsity;
- High spectral resolution;
- Uses single realization of data.

High spectral resolution is essential for the problem under consideration. It comes from the fact that bi-dimensional cisoid of (2) is the same for two ambiguous targets, thus these hypothesis are highly correlated. Different cross-coupling terms can be discriminated only with high spectral resolution.

Recently nonparametric Iterative Adaptive Approach (IAA) was proposed in [5] providing super resolution with arbitrary sampling scheme. In addition, this technique does not require sparsity explicitly and so it can deal more easily than CS with clutter. On the other hand IAA can be seen as iterative estimation of covariance matrix similar to the clairvoyant case discussed earlier. Therefore IAA seems to be a good choice for wideband unambiguous target detection.

III. Iterative Adaptive Approach for Wideband Data

In this section IAA proposed in [5] is revisited for the wideband signal model from the previous section. Denote $\boldsymbol{P}$ a $N_tN_v \times N_tN_v$ diagonal matrix whose diagonal contains the power of scatterer at each possible range and velocity cell. Then i-th diagonal element of $\boldsymbol{P}$ is:

$$\boldsymbol{P}_{i,i} = |\boldsymbol{x}_i|^2 . \tag{8}$$

The noise and interference covariance matrix for target at position i is:

$$\boldsymbol{Q}_i = \boldsymbol{R} - \boldsymbol{P}_{i,i}\boldsymbol{a}(i)\boldsymbol{a}^{\boldsymbol{H}}(i) . \tag{9}$$

Minimizing the weighted least squares cost function with respect to $\boldsymbol{x_i}$ yields:

$$\boldsymbol{x}_i^{IAA} = \frac{\boldsymbol{a}^{\boldsymbol{H}}(i)\boldsymbol{Q}_i^{-1}\boldsymbol{y}}{\boldsymbol{a}^{\boldsymbol{H}}(i)\boldsymbol{Q}_i^{-1}\boldsymbol{a}(i)} . \tag{10}$$

Obtained result looks similar to APES [6], but uses different approach for estimating $\boldsymbol{Q}$, which allows to apply it iteratively. Moreover substituting $\boldsymbol{Q}$ and using matrix inversion lemma, one can obtain:

$$\boldsymbol{x}_i^{IAA} = \frac{\boldsymbol{a}^{\boldsymbol{H}}(i)\boldsymbol{R}^{-1}\boldsymbol{y}}{\boldsymbol{a}^{\boldsymbol{H}}(i)\boldsymbol{R}^{-1}\boldsymbol{a}(i)} , \tag{11}$$

which looks more similar to Capon estimator [7], but also with different way of estimating $\boldsymbol{R}$:

$$\boldsymbol{R} = \boldsymbol{HPH}^{\boldsymbol{H}} . \tag{12}$$

The first estimation of $\boldsymbol{P}$ is obtained by (8) from CI output (7) to start the algorithm.

Equation (11) is IAA formulation for a single snapshot situation which is under consideration. Have started from the first estimation of $\boldsymbol{P}$, IAA computes (12) and (11) for all range and velocity cells until convergence is achieved (according to [5], 15 iterations is usually enough for convergence). Each estimation of $\boldsymbol{P}$, and hence $\boldsymbol{R}$, are obtained from the signal estimated at the previous iteration of the algorithm.

IV. Simulation Results

In this section the ability to discriminate between two competing targets and suppress their ambiguous residuals (sidelobes) is evaluated. The parameters of the radar are described in Table 1. Noise is assumed to be white Gaussian with variance $\sigma^2 = 1/(MK)$, so after processing its power is equal to 0 dB.

True target scene together with output of CI and IAA are shown in Fig. 1. Note that the top three targets do not compete with each other; in contrast, targets at range cells 14 and 15 are competing. As expected the output of CI has many false responses, while the result obtained with IAA shows perfect ability of the approach to resolve ambiguities in multi-target scenario.

TABLE1. Simulated and Experimental data Parameters

Parameter		Simulations	PARSAX data
Waveform			
Carrier frequency	f_c	10 GHz	3.315 GHz
Bandwidth	B	1000 MHz	100 MHz
Range resolution	δR	0.15 m	1.5 m
PRI	T_r	1 ms	1 ms
Ambiguity velocity	V_a	15 m/s	45 m/s
Processing parameters			
Subbands	K	16	16
Pulses	M	16	64
CPI	$M{\cdot}T_r$	0.016 s	0.064 s
Maximum velocity	V_{max}	37.5 m/s	33.75 m/s
Range upsampling	k_t	2	2
Velocity upsampling	k_v	2	2
Range cells	N_t	32	32
Velocity cells	N_v	160	384
Migration at V_a	*migr*	1.6	1.96
Iterations of IAA	*iter*	10	5

V. Detection Study in Semi Experimental Data

The proposed algorithm has been applied to experimental data from PARSAX radar [8] collected in November, 2014 at TU-Delft. Measurement scenario is similar to one described in [9]. The parameters of the data are listed in Table 1.

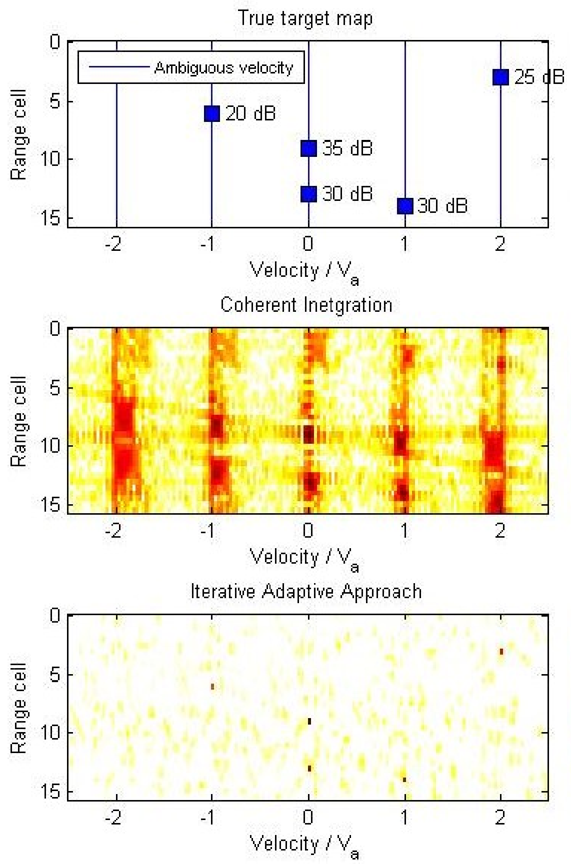

Fig 1. Simulation results for point targets: top – True target map, middle -Coherent Integration,bottom - Iterative Adaptive Approach

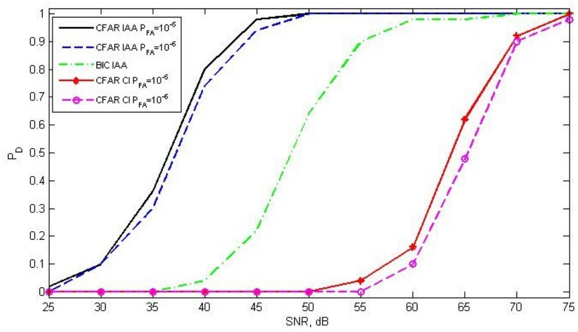

Fig. 2. Detection performance at blind velocity for Coherent integration and Iterative Adaptive Approach

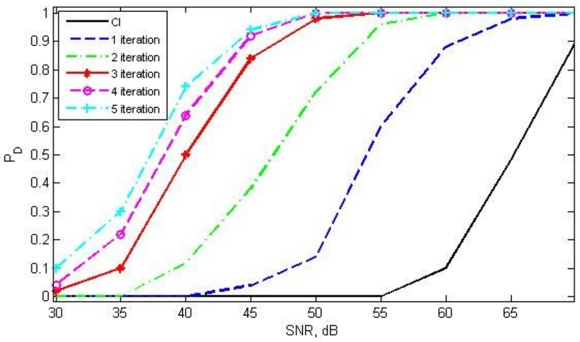

Fig. 3. Detection performance at blind velocity vs iteration

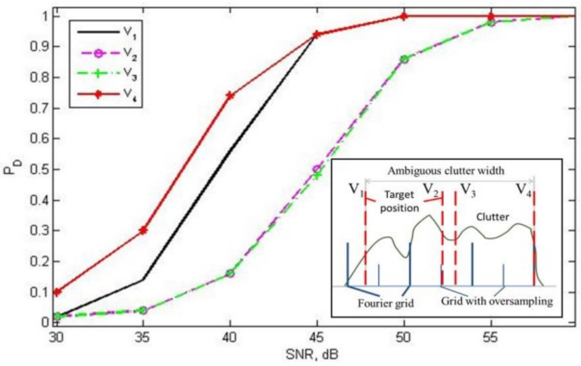

Fig. 4. Detection performance of IAA vs velocity

The data were recorded at the intermediate frequency before range compression. After matched filtering a LRR segment was cut out from the records and FFT on fast-time was applied to obtain experimental data in format similar to (4).

Though the radar system has a lower fractional bandwidth than discussed previously, the range-walk of targets still occurs during the CPI and can be used to remove velocity ambiguities.

The data was used to estimate detection performance at blind velocity. To do so, a synthetic target was inserted into the data (containing real noise and clutter) at blind velocity i.e. at 45 m/s. There should be no real target at this velocity as far as illuminated area contains a highway with velocity limit about 30 m/s. Different realizations of clutter are taken from shifted LRR segments over the range interval containing a highway.

Performances of CFAR detector at the output of CI and IAA together with Bayesian Information Criteria (BIC) [5] applied to IAA output are shown in Fig. 2. A cell averaging (CA) CFAR was used with 3 guard cells in range and 1 guard cells in velocity. Result obtained from 50 different trials shows about 25 dB improvement of similar detectors applied after IAA over the same detectors applied after CI.

For the next two experiments the same scene and CFAR detector with $P_{FA}=10^{-6}$ was used. Fig. 3 shows detection performance vs the number of iterations in IAA. The plots demonstrate the convergence of IAA and emphasize the improvement achieved at the first three iterations of IAA.

The influence of target velocity on detection performance is studied in Fig. 4 and shows a few dB variation within ambiguous sidelobe width. Note that the influence of grid mismatch is negligible (V_2 is on the grid, while V_3 is not).

VI. Conclusions

In this paper we discussed the problem of unambiguous target detection with wideband radar. Iterative Adaptive Approach was revisited and for the first time applied to this problem. Simulation results show great ability of the algorithm to resolve velocity ambiguity. Processing of semi experimental data shows about 25 dB improvements over coherent integration in detection of targets at the blind velocity with moderate migration.

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