Multi-scan spatio-temporal discrimination for small target detection in clutter

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Abstract

Small boats can pose a significant military threat to modern warships and can be hard for radars to detect against a cluttered sea background. This paper describes a novel technique aimed at improving detection performance in these conditions.

The proposed technique works by transforming the gathered radar data into the frequency-spatial frequency (ω-k) space and then modifying the results using a set of matched filters. Inverse matched filters are used to reduce the effects of background clutter by comparing with a defined training dataset. These filtered results are then compared to a set of target-matched filters to identify any target-like tracks.

The algorithm has been tested against measured data and significant improvements in detection performance have been demonstrated. The computations required have been shown to be within the capabilities of modern signal processing cards.

Introduction

Detection of small targets such as fast inshore attack craft is becoming increasingly important for naval operations, as these are often carried out in the littoral zone. Current radar detection performance is limited in littoral conditions and higher sea states where sea clutter prevents reliable target detection and tracking.

Conventional radar clutter reduction techniques such as moving target indication (MTI) or moving target detection (MTD) have little benefit where the target speed is low and contained within the Doppler spread of the sea clutter. This paper describes a novel technique to exploit the long term persistent patterns in the motions of radar sea clutter to allow clutter returns to be filtered to provide enhanced slow target detection. The technique relies on forming a two-dimensional adaptive clutter filter operating in the frequency-spatial frequency (ω-k) sub-space produced from multiple successive scans of radar data. This two dimensional filter allows targets to be distinguished from clutter even if they have the same centre Doppler frequency, due to their differences in spatial frequency spectra.

This approach aims to exploit the difference in the ω-k spectra between targets and clutter by producing an adaptive filter in ω-k space which cancels the persistent sea clutter in the ω-k spectrum, leaving residual target returns visible.

Igence-TWP have also investigated filtering in the ω-k space [1]. Their approach used a ‘scan-to-scan constant false alarm rate (CFAR)’ algorithm that exploited the dispersion relation. Our approach differs in that it attempts to both remove clutter and integrate targets over successive scans and hence has the potential to achieve sub-clutter visibility.

The algorithm

The algorithm uses a target matched filtering operation which exploits the invariance of the target spectra in ω-k space for any given target radial velocity. This allows a bank of filters to be generated in ω-k space, covering the required range of target speeds to be detected.

A process for dealing with very strong targets has been incorporated, which iteratively prunes strong detected targets from the raw data to allow smaller nearby targets to be detected which would otherwise be masked by sidelobes from the larger target.

The algorithm performs target matched filtering using a bank of matched filters in ω-k space for multiple target velocities.

$$F_v(w,k) = \Im\{d^v_{target}(t,r)\}$$

where $d^v_{target}(t,r)$ represents the synthetic target data for target radial velocity v and $F_v(w,k)$ is the corresponding matched filter in ω–k space.

The matched filter output is then transformed into range-time space and the peak output at each cell is selected. The target matched filter output is then given by:

$$MF(t,r) = \max_v\left[\frac{\left|\Im\{d_{test}(t,r).F_v(w,k)\}\right|}{G_{final}(v)}\right]$$

where $\max_v$ indicates the maximum value across the target radial velocities and d_{test} is the signal strength in the test region.

G_{final} is given by the median of the target matched filter response to the training data samples:

$$G_{final}(v) = \widetilde{G}_{sample}(v)$$

$$G_{sample}(v) =$$
$$\max_{t,r}\left(\left|\Im\{d_{training\_sample}(t,r).F_v(w,k)\}\right|\right)$$

where $d_{training\_sample}$ is one sample of training data over an interval of range-time space and $\max_{t,r}$ is the maximum value of the function taken over range-time space.

The maximum filter velocity at each range-time cell is recorded as an array $v(t,r)$. The strongest signal is found and if this exceeds a threshold then the data at the position of the equivalent matched target in range-time space are set equal to the mean of the data from the surrounding range cells:

If

$$\max(MF(t,r)) > T_2$$

then

The target positions to be excised from the data are given by

$v_{\max} = v(t_{\max}.r_{\max})$

where t_{max} is the scan time corresponding to the maximum value of the matched filtered output and r_{max} is the range cell corresponding to the maximum value of the matched filtered output.

The position of the equivalent large target is given by

$$r_{target}(t) = r_{\max} + (t - t_{\max}).v_{\max}\tau_{scan}$$

The target pruned data for the range cells within L range cells either side of the detected large target is interpolated from the surrounding cells as:

$$\left|r - r_{target}(t)\right| < L$$

$$d_{pruned}(t,r) = d_{test}(t, r_{target}(t) - L) + \left[\begin{array}{l} d_{test}(t, r_{target}(t) + L) \\ - d_{test}(t, r_{target}(t) - L) \end{array}\right] . \left[\frac{r - (r_{target}(t) - L)}{2L}\right]$$

and elsewhere:

$$\left|r - r_{target}(t)\right| \ge L$$

$$d_{pruned}(t,r) = d_{test}(t,r)$$

The whole whitening and matched filter process is then repeated using the pruned data.

The algorithm produces a whole swath of range-time data. Typically only a single time estimate is required and this can be extracted from the swath:

$$Filtered\_estimate(r) = MF_{final}(t_{estimate}, r)$$

where $t_{estimate}$ is the scan time the estimate is produced for. With each successive scan, the filtered estimate is updated using a swath of preceding scans along with the latest. The process is repeated for each azimuth angle to build up a full range-azimuth picture on each scan.

Results

The effectiveness of the algorithm was tested using radar data gathered during a series of small boat trials, the first with an experimental military radar.

Figure 1 shows a range-time slice for the measured targets in a clutter limited environment. The filtered data results show a significant enhancement to the raw data, with all three targets clearly visible and a fourth stationary target also clearly visible.

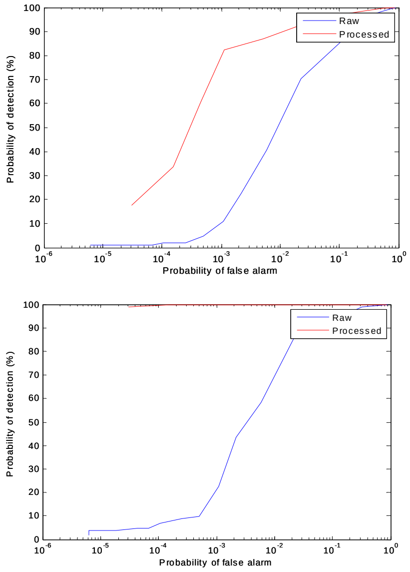


Figure 2 - ROC curves for two of the four targets

To quantify the improvements gained, receiver operating characteristic (ROC) curves were calculated for each target. As

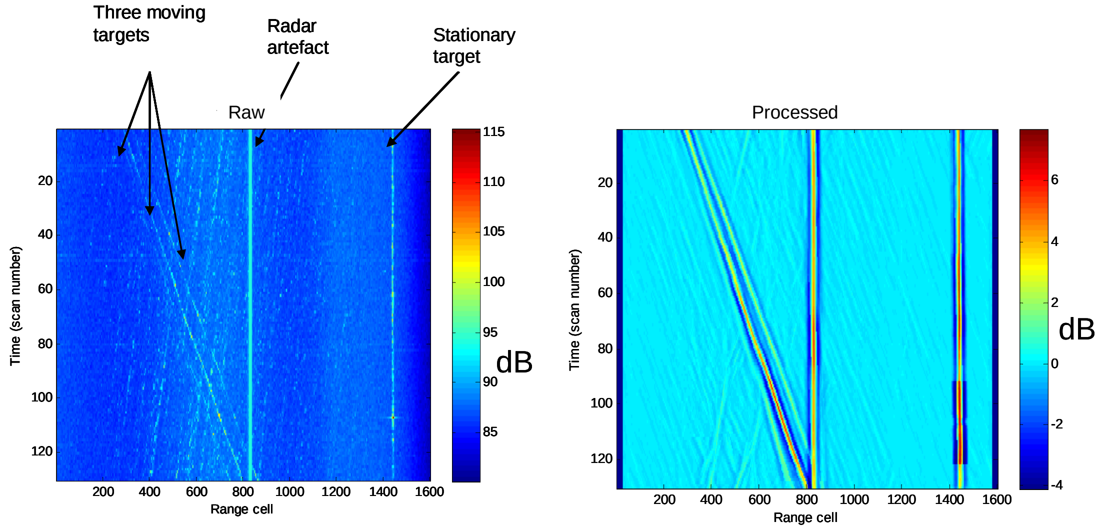


Figure 1 - range-time slice of example targets in a clutter limited environment. Raw data are shown on the left and processed data on the right.

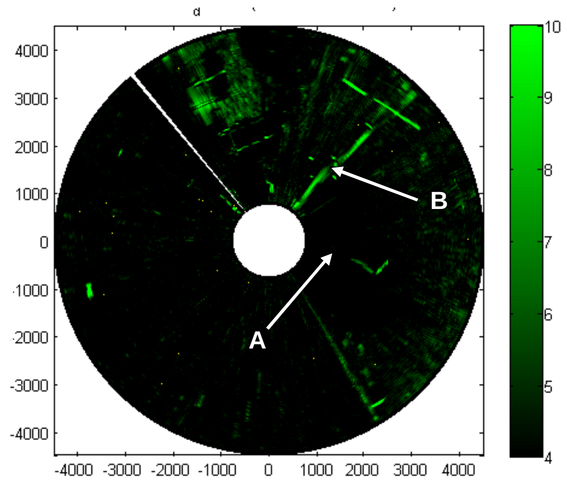


Figure 4 - filtered MOT image showing cases where the proposed algorithm loses track

can be seen from Figure 2, there was a 10 dB reduction in false alarm rate for the first target and up to 30 dB reduction was observed for the other three.

The second set of results came from a trial using a commercial navigation radar.

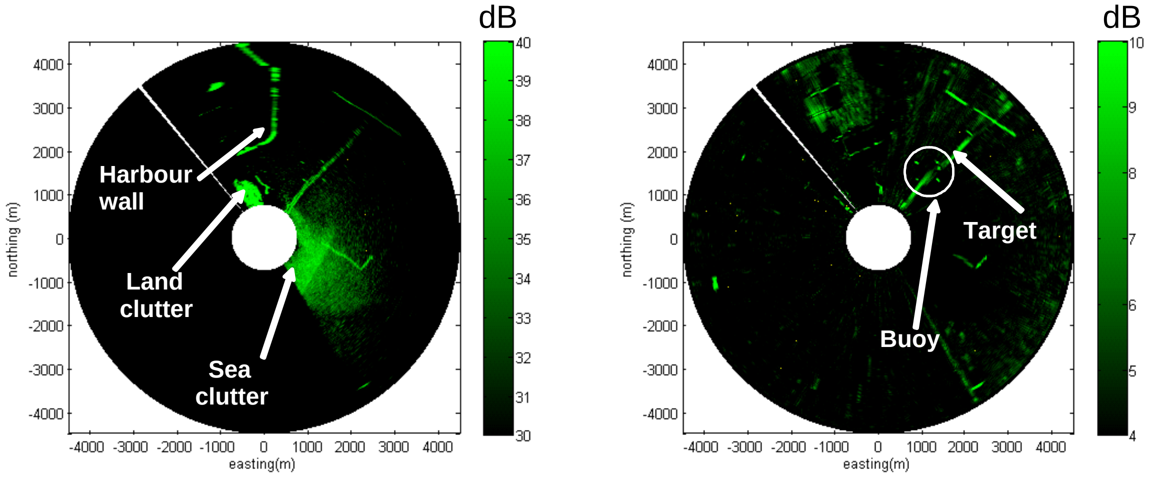
Figure 3 shows a maximum over time (MOT) image of the raw (left) and filtered (right) measurements. This form of image summarises the time history over all angles and ranges by assigning each cell in the image the maximum value it attains over the time sequence being studied. In the filtered dataset shown on the right of Figure 3, the clutter from the land and sea are almost entirely suppressed, as is the harbour wall. The relative returns from the targets of interest are enhanced.

However, there are some quirks in the filtered results which illustrate the constraints on the proposed algorithm. These are labelled A and B in Figure 4. In case A, the L-shaped track appears prematurely truncated compared to the raw data and in case B there is significant fading of the tracks of the boats near the buoys.

In case A, the track is truncated as a result of the choice of training data. In this case, the target path was inadvertently included in the training data set and hence was “trained out”. A more advanced training dataset generation algorithm would help to resolve this issue. In case B, the target is (briefly) moving at the same radial velocity as the clutter in that region, so its signal is suppressed along with that of the clutter.

Computational requirements

To estimate the potential trade-offs involved in implementing the proposed algorithm on current and future systems, the signal processing gain was estimated for the



Raw

Filtered

Figure 3 - comparison of raw (left) and filtered (right) data

algorithm with a variety of parameter choices and compared to the estimated processing load requirements. The algorithm parameters considered in each case are listed in Table 1. As can be seen from Figure 5, any variant of the algorithm using fewer than 10 time scans in the matched filters is well within the reach of a modern signal processing board. This suggests that a practical implementation of the proposed algorithm should be achievable on a modern radar system.

Conclusions

A new signal processing technique has been developed to improve radar detection of small targets. It works by transforming the gathered radar data into the frequency-spatial frequency (ω-k) space and then modifying the results using a set of matched filters. Inverse matched filters are used to reduce the effects of background clutter by comparing with a defined training dataset. These filtered results are then compared to a set of target-matched filters to identify any target-like tracks.

The algorithm has been tested against measured data from trials; significant performance gains were observed compared to the raw data.

The potential for implementing the proposed algorithm on existing and future hardware has also been assessed. The computational requirements of different algorithm variants have been estimated and are within reach of commercially available signal processing cards.

Parameter set ID	A	B	C	E	F
Number of scans	5	10	20	30	40
Number of velocity bins	14	27	54	81	108
Range cells in matched filter	300	300	300	300	300
Total range cells to be processed	1600	1600	1600	1600	1600
Number of targets extracted	1, 5	1, 5	1, 5	1, 5	1, 5
Rotation rate (Hz)	0.5	0.5	0.5	0.5	0.5
Azimuth sample spacing (degrees)	3	3	3	3	3

Table 1 – algorithm parameters considered in performance assessment

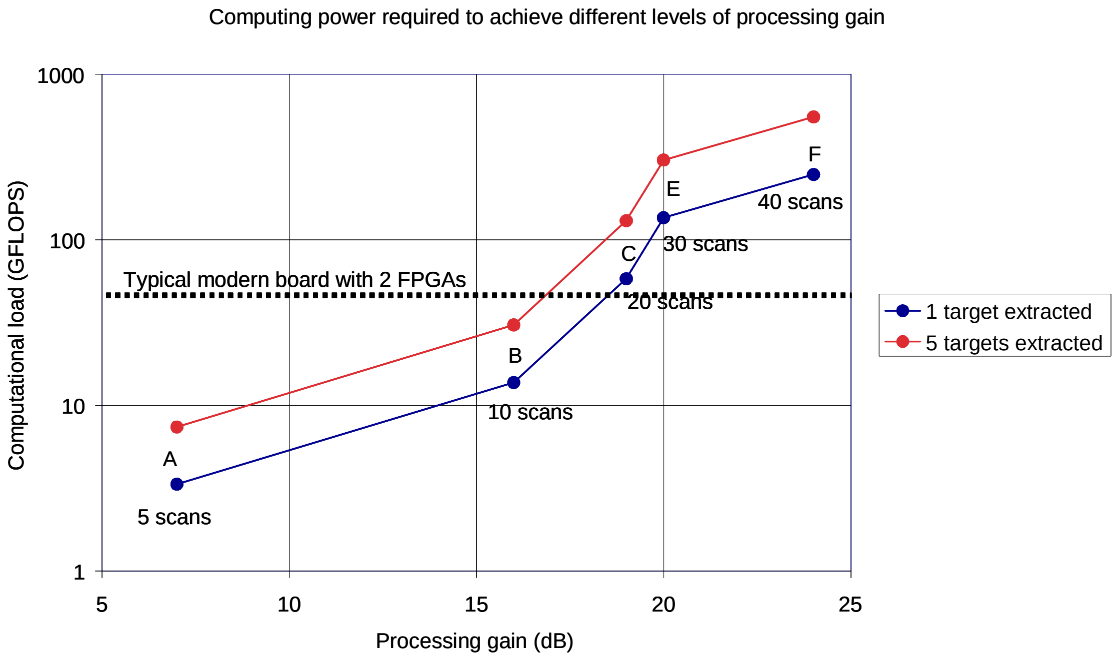


Figure 5 – computational power needed to achieve different levels of signal processing gain

References

1. K D Ward et al: "Sea clutter transient spatial coherence and scan-to-scan constant false alarm rate". IET Radar Sonar Navig., 2007, 1, (6), pp. 425–430.

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