WAVEFORM PROCESSING-DOMAIN DIVERSITY AND ATR

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ABSTRACT

Classification of targets by radar has proved to be notoriously difficult with the best systems still yet to attain sufficiently high levels of performance and reliability. In this paper we take cues from nature to propose and examine a novel approach to target classification, based on diversity, as applied in the waveform processing domain. In the new approach, data is processed in multiple, different, forms, in parallel. The two forms that we have exploited in this work are the time and space domains. Most classification and Radar image analysis algorithms handle Radar data in the space domain only. Using simulation studies, we first show that phase or k-space data contains additional information. It is also shown that, counter-intuitively, having a sharp spatial Radar image (with reduced side-lobes) in fact worsens classification performance. Lastly, the proposed architecture is validated against a traditional, unitary based classification scheme.

1. INTRODUCTION

Robust and reliable target classification using radar systems has long been a goal of researchers. However, this has remained somewhat elusive. The complexity of the scattering environment together with target echoes being extremely aspect sensitive combine to make this a highly challenging task. Nonetheless, there have been very creditable attempts, primarily exploiting very high resolution in either or both range and cross range. These utilize a variety of processing approaches including statistical, Artificial Intelligence and pattern recognition. Many of these approaches are summarized in the excellent texts by Rihaczek [1] and Tait [2].

More recently, the concept of cognition has been advocated as offering new and improved performance for radar in a variety of ways [3]. Cognition means ‘knowing’ and can be thought of as the process by which we know about the world. Here we develop an approach that tends towards synthetic cognition, utilizing two major characteristics that exploit waveform diversity. Firstly, the sensor parameters to be transmitted should be variable, so that they can be altered to acquire the most useful information. Secondly, the setting of those parameters and the collection of sensor data is carried out using prior information regarding the object or scene under observation, as well as the sensor data collected in previous time intervals. In this way we invoke the concepts of the functioning of biological memory in a much wider sense than normally used. Of course, this is all done to achieve a desired goal. We note here that the definition of cognitive behaviour, and, when can a system be called cognitive, are still areas of intense debate [4]. Hence, what we are really doing is to take different cues from cognitive and bio-inspired mammalian systems (such as the human being and the bat) and applying them in the field of radar sensor processing, with the aim of enhancing performance. In a strict sense, such a system can at best be called smart, bio-inspired or adaptive.

In this paper we introduce a new form of processor in which echo data is manipulated in a number of parallel channels, allowing forms of differing information to be extracted in multiple domains, such as time (i.e. high range resolution profiles), frequency and space. We take cues from many sources, for example, noting that bats use frequency modulated waveforms suggest that they are able to recognize targets from spectral notches and peaks in the complex echo [5,6]. Vespe et al. [7] show that spatial diversity improves classification performance, by acquiring data from multiple independent looks (spatial diversity). The results of extracting information in parallel data channels combined with those stored in memory enable an estimate to be derived, from which a classification decision can be made. A declaration of a correctly classified target is only made if the estimate exceeds a given threshold. If not, the processor evaluates the information to determine any short-fall and adjusts the radar parameters to collect revised information (e.g. more precisely estimating target length) against a chosen threshold. This process continues until a decision can be made.

The rest of the paper is organised as follows: the next section deals with simulation results which establish the fact that phase or k-space domain data contains useful information about the scene which is not captured well in the amplitude or space domain. We also show that the often ignored sidelobes in radar data possess information which helps in target recognition. The section following describes the new ATR architecture and the experimental setup. Subsequently the results from the ‘cognitive’ processor are discussed andthe paper ends with a some thoughts as to the future possibilities of this new form of processing architecture for ATR.

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2. PROCESSING DOMAIN AND INFORMATION CONTENT

For target recognition, Radar engineers have, in the main, utilized high range-resolution (HRR) profiles or high-resolution synthetic aperture radar (SAR, also inverse SAR) images also that provide cross range information. Traditionally, space domain data has been given more importance and a crisp HRR profile or SAR image is preferred to a signal representation with poor side-lobes. In this section, we introduce a few simulation exercises which show that phase or k-space domain data sometimes can have information which is missed in the space domain. We also show that ignoring and suppressing side-lobes may result in an image with greater visual appeal but may worsen the ATR performance.

2.1 Space and frequency domain data

We synthesized a scene consisting of three clusters of scatterers. In each cluster there were four basic scatterers i.e. a dihedral, a corner-reflecter, a cylinder and a sphere. We have simulated these for a bandwidth of 500MHz, centered around 5GHz. Four different scenes were simulated, such that each scene has the three clusters at the same positions but consisting of different types of scatterer. Each cluster occupies only one resolution cell in the space domain, so that it will appear as a single, strong scatterer. The detailed modelling steps can be found in [8]. Figure 1shows the response from the targets in the space and frequency domains. As can be observed, although the space domain shows just three scatterers, the frequency domain displays completely different behavior for each of the scenes. This indicates that the frequency domain can help provide another dimension of discriminating information about the scene which can potentially be used to enhance the classification performance. Note that the frequency domain is only complimentary to the space domain, and both the domains need to be analysed using different processing approaches. This gives us the motivation to propose the waveform processing-diversity strategy for ATR.

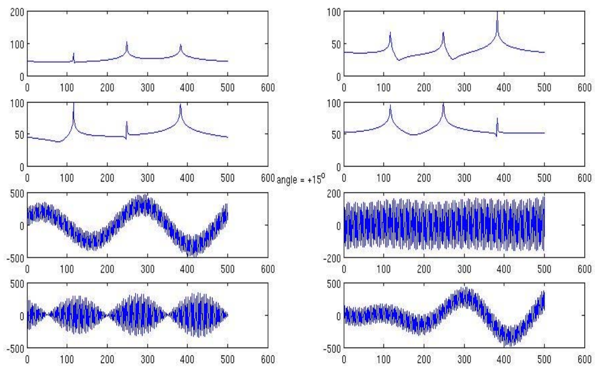


Figure 1 – Data from four different scenes in the space and frequency domain. The top four plots show the data in the space domain and the lower four plots show the corresponding data in the phase domain

2.2 Sidelobe and ATR

In a second set of simulation exercises, we show that the information contained in sidelobes is also potentially important for classifying targets. Generally, the sidelobes in an HRR profile or a SAR image are suppressed in the preprocessing stage. However, as shown in the last subsection, the information associated with the major scattering centers is not always sufficient to characterize the target. Some classification-specific information may also be contained in the side-lobes. To validate this, we ran ATR simulations on the MSTAR [9] dataset for five of the targets. Then we applied various sidelobe reduction algorithms [12,13] to 'improve' the images. The naive nearest neighbour classification algorithm has been used to classify the targets [15]. Details concerning the confusion matrix derivation can be found in a paper by Mishra et al.[16]. As can be seen from Figures 2 and 3, suppressing the sidelobes does enhance the appearance of the SAR images. However, this also deteriorates the ATR performance, as evidenced by the confusion matrices corresponding to the figures. This shows the importance of sidelobes for ATR. However, if the sidelobes are to be preserved, the intelligibility of the mainlobes will reduce. Hence, a way to have both the sidelobe and the mainlobe information is to process the data in both the space and frequency domains.

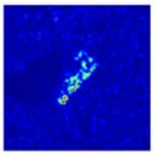
3. SYSTEM ARCHITECTURE FOR WAVEFORM PROCESSING-DOMAIN ATR

Figure 3 shows a schematic of the proposed architecture. It is important to understand that this form of processor is rooted in observations of mammalian systems such as Bats and Dolphins that use echo location. However, it can be designed analytically and this, ultimately, will provide rigour in the generalisation of such processing approaches. Secondly, such an architecture, although presented here for radar based target recognition, can successfully be extrapolated to a broader set of sensing and motor systems which try to emulate human behaviour.

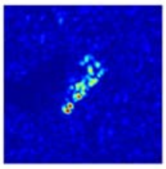
The major blocks (each representing a sub-system of the proposed architecture) are as follows.

1. *Radar platform:* This block represents the sensor-platform and is also responsible for any preprocessing required for the signal collected by the platform. Once the diversity decisions are made, this block has the responsibility to change the parameters of operation accordingly I.e. the emitted waveforms, platform location, etc. In the current work, we have dealt with angular diversity only.
2. *Range domain processing:* This block handles the processing of the range profiles as collected from the sensor platform.
3. *Frequency domain processing:* This block handles the processing of the data in the frequency domain.

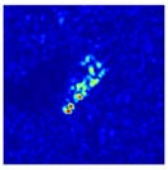
4. *Confidence calculation:* This block handles the features and information collected from the above two blocks to make a decision regarding the type of target in the scene along with a confidence with which this decision is made. This confidence level representation



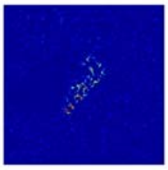
	Tg1	Tg2	Tg3	Tg4	Tg5
Tg1	211	1	20	41	1
Tg2	4	258	4	2	6
Tg3	11	4	222	10	26
Tg4	18	1	8	242	5
Tg5	2	15	9	4	244



	Tg 1	Tg 2	Tg 3	Tg 4	Tg5
Tg 1	204	1	23	45	1
Tg 2	5	250	2	4	13
Tg 3	11	7	212	12	31
Tg 4	25	3	8	231	7
Tg 5	3	19	12	4	236



	Tg1	Tg2	Tg3	Tg4	Tg5
Tg1	200	1	22	48	3
Tg2	6	252	2	3	11
Tg3	12	7	212	14	28
Tg4	23	2	9	234	6
Tg5	2	19	12	4	237



	Tg 1	Tg 2	Tg 3	Tg 4	Tg 5
Tg 1	184	8	17	57	8
Tg 2	14	210	12	8	30
Tg 3	23	15	174	30	31
Tg 4	41	9	18	190	16
Tg 5	8	42	28	11	185

Figure 2 Effect of windowing on image quality and on classification performance. Top to down: Sample of original SAR image; after Hamming windowing; after nonlinear apodization [12]; after refined nonlinear apodization [13].

can be in terms of a continuous variable such as probability, or, in terms of simple discrete levels such as *CONFIDENT* or *NOT CONFIDENT*.

5. *Memory:* Memory description and usage is a crucial part for any automated system endeavouring to become cognitive. However, in the form of processor invoked here, the current memory block only supplies prior test-phase based information to block 4 and block 6.

6. *Decision maker:* This block takes the decision regarding whether to go for a fresh collection of data from the scene or not, and, deciding what diversity is to be employed for the fresh data-collection step.

Note that the fifth block is the memory block containing both short and long term memory consistent with biological observations. Further details of the algorithm can be found in a paper by Mishra et al.[14].

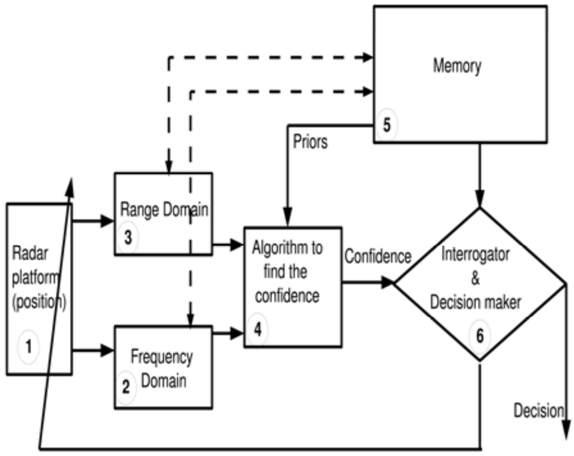


Figure 3: The processing architecture

3.1 Description of experimental setup and algorithm

Simulated echo data have been created from two sources. The first is via analytical solutions for the EM scattering from simple targets (spheres). The second is via a computational EM simulation tool FEKO [10,11]. These provide the source of raw data to be interrogated by the cognitive processor. In the first case, simple targets have been chosen to help provide a physical insight as to the scope of improvement in classification performance. Firstly we consider only the azimuth angle variation capability of the system and investigate the algorithms to be used in the central processor and the potential performance enhancement, as compared to traditional range profile based target recognition systems. Secondly, we investigate the potential of using the phase part of the frequency response of the target. For a linear FM radar the raw signal in *k* space is the frequency response of the target.

4. PROCESSING AND RESULTS

The first phase, where the ATR capabilities of the newly proposed architecture were tested, was limited the diversity to azimuthal angle variations only. For a given pose, the system calculates the possible class of the target. It also supplies a confidence level to this decision. Depending upon this confidence level a decision is made regarding if a further profile to be collected for a different orientation of the target, i.e. from a different azimuth-angle. The re-positioning of the radar allows for a different viewing angle from which additional information can be gleaned. This input is combined with previous pulses, using information stored in echoic memory.

The long-term memory is utilized if the radar recognizes the current scenario as having similar attributes to that of a previous case. This is used to change the bias weighting in the decision maker accordingly. The process is continued until either a classification decision is made with a desired confidence, or, a maximum number of profiles have been checked, without being able to give the desired confidence level to any of the classes.

In the limited simulation done to date, we have tested three types of data processing. In the first type, data in time/space domain, i.e. range resolution profile data, is handled. This is similar to conventional ATR processing methods. In the second type, both time and frequency domain data is handled simultaneously. This will be referred to as time-frequency domain algo 1. In the third type, decision is tried to reach with the desired confidence, using time domain data only. In case no single class scores the desired number of votes, then data in the frequency domain are processed to bolster the decision making. This will be referred to as time-frequency domain algo 2. The change of performance of classification for both the cases were plotted against the angle by which the consecutive perspectives differ ($\Delta\theta$). The results are summarized in Figure 4.

We see that using both the channels (Blocks 2 and 3) gives better performance than using a single channel. The conventional algorithm of single perspective based ATR is when $\Delta\theta = 0$.

Secondly, the performance was the best for a jump of around 5-8 degrees and using both the channels, give better performance. We note that on an average (median) profiles from three different perspectives are enough to give a decision with practical confidence level. For each $\Delta\theta$, the median number of perspectives taken by the algorithms is also noted. Irrespective of the value of $\Delta\theta$, the median number of perspectives was found to be 3. Secondly, as compared to the proposed variable perspective ATR scheme, if only two perspectives were used with, the performance was found to be 85%. Hence, the bio-inspired framework performs better than both the single perspective ATR scheme, as well as the fixed-number, multi-perspective based scheme.

An anomaly in the result is the observation that for $\Delta\theta = 0$ the conventional algorithm performs better than Algorithm 2. This is mainly because, with $\Delta\theta = 0$, there is no extra spatial formation added with iteration. Handling the information from the two channels may also confuse the classifier. This negative effect is substantial enough for Algorithm 2 so as to make it perform worse than the conventional algorithm.

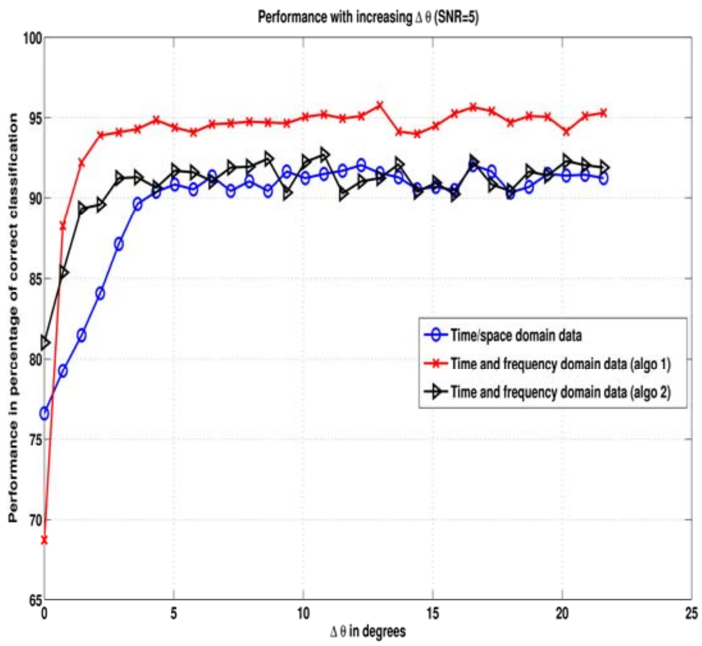


Figure 4: Results from the proposed architecture as compared with conventional ATR algorithms

5. CONCLUSION

This research has introduced the concept of a highly dimensioned, feed-back based processing architecture that has roots in observations of the operation of biological systems. A central aspect is the use of waveform and spatial diversity to provide a richer information source from the scene under interrogation. We show that a successful ATR algorithm benefits from both space and frequency domain processing of Radar data. Inspired by t,his we have proposed an ATR architecture which implements this waveform processing-domain diversity.

We also show that the proposed architecture performs better than the established ATR algorithms. Note that the current work has only exploited a part of the proposed architecture. The architecture can be exploited in a more exhaustive manner, which in turn, could provide enhanced ATR performance.

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