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Cognitive Radar - Enabling Techniques for Next Generation Radar Systems

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Abstract: *Cognitive radar is a young discipline with the claim to open the door for next generation radar systems providing a higher efficiency, robust operation via intelligent choice of radar actions, and even a high degree of autonomy. The ideas behind are collected in the two most influential textbooks by Haykin [1] and Guerci [2]. Both contain also experimental results while there are not much papers else presenting real world experience. In this paper we summarize the general approach and discuss two examples for application of cognitive radar.*

1. Introduction

Today's radar systems have reached a level from which new big goals may be set, which are nevertheless realizable in the in the foreseeable future. The necessary tools are available: real time processing even for sophisticated algorithms with powerful processors, multifunction phased array systems - with their arbitrary beam steering an ideal platform for the solution of complex surveillance and reconnaissance tasks. Arbitrary waveforms with large bandwidths can be generated and transmitted. And: everything is programmable, i.e. we may speak of 'software-defined radar'. Last but not least low-weight high-speed memories with gigantic capacities are available, an important basis for knowledge-based processing. One of the next big goals is to realize radar systems which can be called *cognitive* in analogy to the cognitive abilities of human beings and many animals.

The statement of the cognitive radar pioneer Simon Haykin '*it is indeed feasible to build a cognitive radar system using today's technology.*' [3] certainly is true. Cognitive radar aims to optimize radar performance by intelligent adaption of all radar steering and operational parameters in response to properties of the environment available from internal of external knowledge or even learned by the system during operation. Joseph Guerci declares a goal of implementing tools that make the radar capable of '*sensing, learning, and adapting to complex situations with performance approaching or exceeding that achievable by a subject matter expert, especially for real time operations which demand automation*' [2, 4].

Future radars should posses more 'intelligence' - whatever this means. We wish to get more performance out of existing handware by optimized use of resources, or vice versa maximization of the information gain per time unit. Perhaps we also want to get more autonomy to disburden the operator at least with low-level decisions as the selection of operational modes, but also as better preparation for more momentous actions. The system should be able to learn from successes or failures at former radar decisions. Further new architectures and signal processing tools (as MIMO-radar or compressive sensing) demand very complex decisions to evolute their potentials also in time-critical situations. Finally the radar system could even pilot unmanned platforms or give recommendations for this to optimize the radar performance.

Cognitive radar has been studied for different applications: Adaptive waveform generation [5, 6], e.g. for the enhancement of the signal-to-clutter+noise ratio, optimization of radar networks [7, 8], passive coherent location [9], moving target detection with STAP [4],target tracking [10, 11], operation in spectrally dense environments [12, 13, 14], channels parameter estimation [15], MIMO radar [4, 16], electronic counter-counter measures [17] and others. There are also efforts to combine cognitive radar with compressive sensing techniques [18]. Experimental verifications are still rare.

2. Attributes of cognitive systems and radar

Even though the books by Haykin and Guerci share the notion of continuous performance improvement through a feedback principle between receiver and transmitter, there is still no generally accepted definition of where exactly the borderline between a traditional and a cognitive radar lies. There are however several established technologies that can be considered key enables for the ultimate goal of automating most of the supervision and control tasks, that currently still mainly rely on radar operator experience and skillset. The list comprises (and is not limited to) waveform diversity, channel estimation, knowledge-aided processing, resource-management and optimization technologies, spectrum management and cognitive radio, pattern recognition and deep learning approaches, appropriate hardware and real-time processing capacities and - of course - a suited system-architecture and operational concept that connects all the bits and pieces!

Most authors refer to human cognition as a source of inspiration for the realization of cognitive capabilities in a radar system. In [1] the following definition can be found: *We say that a dynamic system, operating in an environment to be explored, is cognitive if it is capable of four fundamental functions (tasks) that are basic to human cognition: (1) the perception-action cycle, (2) memory, (3) attention, and (4) intelligence.* All four cognitive functions should be present and interact, whereas ’intelligence’ is certainly most difficult to grasp!

At Fraunhofer FHR, we motivate our cognitive radar architecture by the Rasmussen-Model of human cognitive performance [19], which is used in cognitive psychology, human factors engineering and robotics. It asserts that intelligent, goal-oriented human behavior emerges from several perception - action cycles that are continuously active on three layers with different levels of abstraction. The three layers here are with ascending abstraction level: the skill-based layer (signal generation (A) - signal processing (R)), the rule-based layer (recognition (R) - task scheduling (A)) and the knowledge-based layer (situational awareness (R) - plans (A)). Here,

(A) and (R) denote the actuator-branch or reception-branch, respectively, which map the model to the radar application, see Fig. 1. The skill-based layer corresponds to continuous signal-generation and processing processes. The rule-based layer enriches the semantic content of the perceived data by means of information processing, such as target classification techniques or inference of a threat state by geometrical considerations. A pre-stored decision rule ('policy') then maps this symbolic state information into an immediate reaction to be executed by the transmitter. The knowledge-based layer represents the highest level of abstraction, incorporating all the information and knowledge that is available in the system, including e.g. platform state and mission goals. A knowledge-based reaction is found by online planning and deliberation from first principles on the available knowledge, which is computationally most demanding but also most flexible to unforeseen situations. The model provides an upward path of information aggregation and a corresponding downward flow of decision making, which is common to sensor fusion (e.g. the revised JDL model [20]). Yet, there are several subtle differences, e.g. the explicit representation of goals and the control flow between the subfunctions and layers, that resemble more a hybrid robotic control architecture [21]. In the remainder of this article, we will give two examples of radar tasks that implement the perception-action cycle on the skill and rule-based layer.

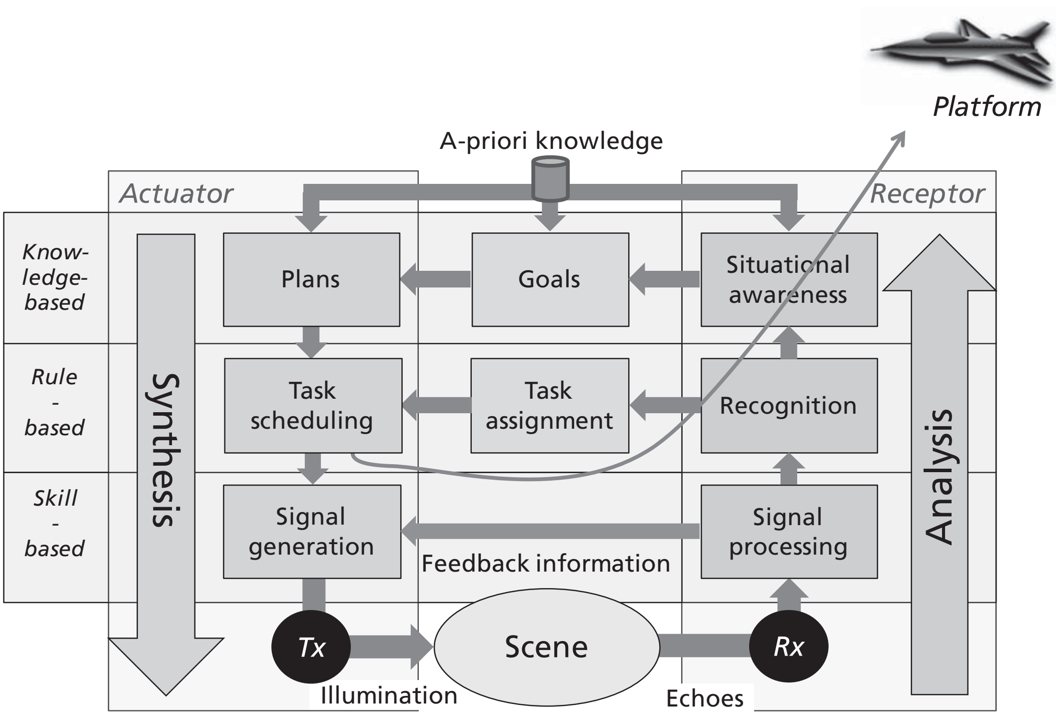


Figure 1: Three level model of cognitive radar deduced by the general model of Rasmussen

3. The perception-action cycle is a key ingredient to cognitive radar

For general cognitive systems, the perception-action cycle can be characterized as follows, see Fig. 2: The main task of such a system - regardless weather human being or machine - is to explore the environment. Thus, the actuator generates *stimuli* to get a response from it, for radar are these the emitted waveforms. The response (radar: echo) is gathered by the perceptor - for humans by the sensory organs, for radar by the receiver. Decisive is the feedback-information about the gained information to the actuator, to trigger further actions. Most of existing radars don't make use of the feedback in a systematic manner - further actions (e.g. type of waveforms) are more or less independent of the past.

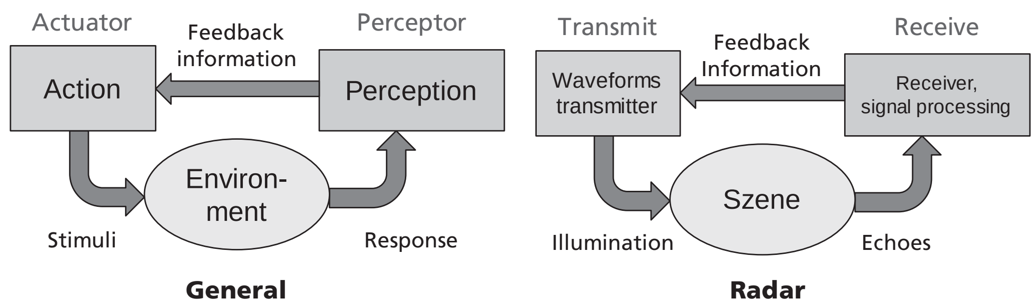


Figure 2: The perception - action cycle in general - also for human beings, and with respect to radar, see [1]

There are several ways to close the feedback loop on the side of the transmitter to optimize some performance criteria. They range from prestored reaction rules to stochastic control theory. Of particular importance to the field of cognitive radar is the application of Markov-Decision-Processes (MPDs) or Partially Observable Markov Decision Processes (POMDPs). As shown in Fig. 3, MDPs are a natural extension to model Markov processes that can be influenced by the execution of an action $\mathbf{A}_i$ in state $\mathbf{S}_i$ that gives a reward $\mathbf{R}_i$. The solution to a MDP is a decision policy that maps each possible state $\mathbf{S}_i$ to an optimal action $\mathbf{A}_i$ that maximizes the expected reward. The concept can be extended for partially observable states by using POMPDs which are, however, more difficult to solve. In his book [1], Haykin applied the approach to derive optimal waveforms with respect to chirp-rate and pulse-length as actions to optimize tracking state estimation error. However, it is clear that any radar task, whose state fulfills the Markov-property, and that can be influenced by executing actions for which some estimated performance metric is available, can be optimally controlled by MDPs or POMDPs.

4. Cognitive target classification

An early example of using this approach was given by Castanon [22] for target classification, e.g. for airborne surveillance. The objective is to select between a low resolution (Mode 1, RCS measurement) and a high resolution (Mode 2, Imaging) sensor mode to be applied to a scenario that contained three different classes of targets $K = \{1, 2, 3\}$, whereas the correct declaration

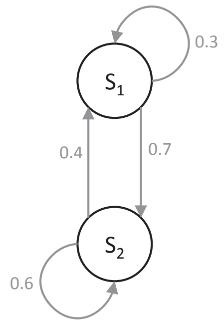
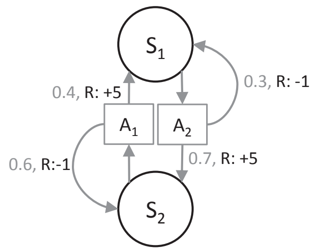
Markov Models		*Do we have control over the state transitions?*	
		No	Yes
Are the states completely observable?	Yes	***Markov Chain***	***Markov Decision Process (MDP)***
	No	***Hidden Markov Model (HMM)***	***Partially Observable Markov Decision Process (POMDP)***
Example of fully observable markov models *(HMM / POMDP analogous)*		 Markov Chain with two states	 MDP with two states and two actions

Figure 3: Markov decision processes are as important to cognitive radar as markov chains are to traditional radar. Modified from [23]

of class 1 ($v = 1$) was the prime goal. The cost function hence gave a higher penalty of $c = 2$ to missed detections of target class 1 (*md*) and smaller penalty of $c = 1$ for targets of class 2 or 3 that were erroneous declared as class 1 (*fa*).

Fig. 4 shows the initial results of a simulation of 100000 targets done at FHR in which up to five subsequent illuminations of a target with either the low or high resolution sensor mode where fused using the Bayes theorem. The problem was modeled as a MDP with state variables containing the likelihood for each target class, actions representing a target illumination with sensor mode 1 and 2, and the expected cost after the final declaration. The tree structure shown in the upper right shows the optimal decision policy for selecting the next sensor mode as a result of the previous classification (measurement $Y = \{1, 2\}$). The comparison of results in the lower left corner of the figure shows the actual cost incurred with respect to sensor mode selection strategy and the maximum allowed number of subsequent classifications for a target. The graph shows, that the dynamic selection of sensor modes according to the optimal decision policy outperforms the static application of mode 1 or 2 or random toggling.

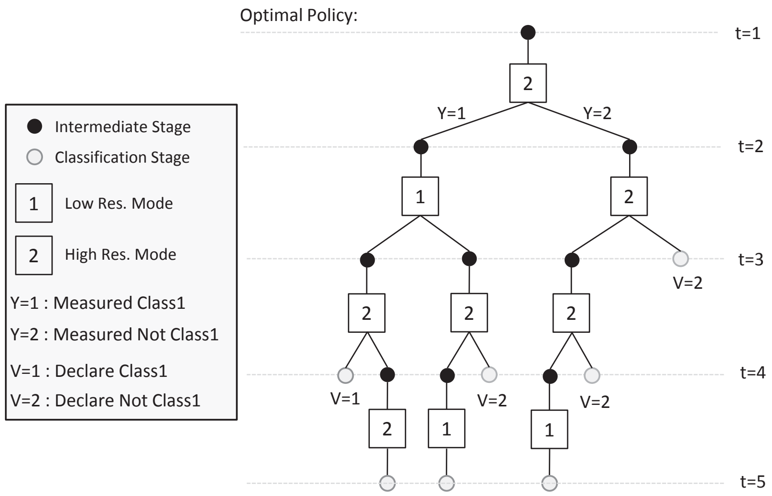
Even though this example could be augmented further by considering sensor mode resource consumption, it does indicate how the feedback mechanism of the perception-action cycle can increase the performance of typical radar tasks.

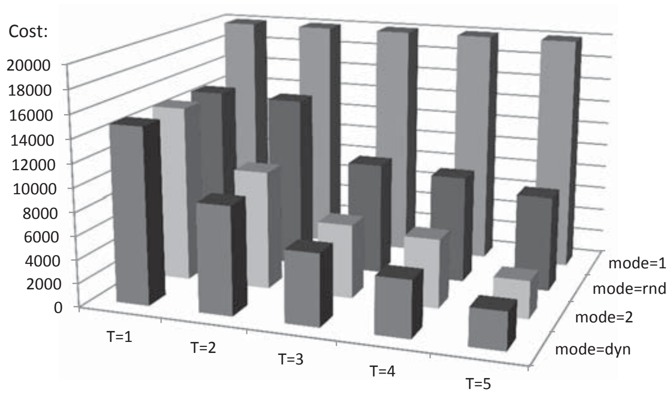
Confusion Matrix:

Mode 1	K=1	K=2	K=3
V=1	0.9	0.9	0.1
V=2	0.1	0.1	0.9

Mode 2	K=1	K=2	K=3
V=1	0.75	0.15	0.1
V=2	0.25	0.85	0.9

Cost	K=1	K=2	K=3
V=1	0 *(cc)*	1 *(fa)*	1 *(fa)*
V=2	2 *(md)*	0 *(cc)*	0 *(cc)*





Scenario:
- 3 Target Classes (K=1,2,3)
- 2 Radar Modes (Low / High Res.)

Objective:
- Classify Class1 and Not Class1
- Penalty 2 for missed detection
- Penalty 1 for false alarm

Figure 4: Closed-loop classification using MDPs

5. Cognitive MIMO for ground moving target recognition

GMTI for airborne multi-channel radar systems applies Space-Time Adaptive Processing (STAP) by adaptive estimation of the space-time covariance matrix. This step may be regarded already a part of cognitive operation, since it implicitly learns properties of the environment (here: ground clutter) and uses this for signal processing. Nevertheless it is classically limited to the receive channel; the transmitter (wave form) and the transmit antenna are commonly driven in a routine mode, for instance by use of chirp waveforms and scanned beams - not regarding the momentary clutter properties.

Cognitive procedures for GMTI, optimizing simultaneously the Tx and Rx channels, have already been proposed in literature, also for array antennas in MIMO configurations [4]. Referring to the terminology introduced in chapter 3, we will present some additional contributions to this matter addressing techniques adequate to commonly used phased-array frontends (possibly with small modifications) and real-time operation.

We have in mind an antenna of the type illustrated in Fig. 5 left. It is a fully equipped phased array antenna with phase shifters whose aperture is divided into a few subarrays in motion direction. The only difference to a traditional multi-channel architecture is that in Tx the N subapertures are driven by individual wave form generators.

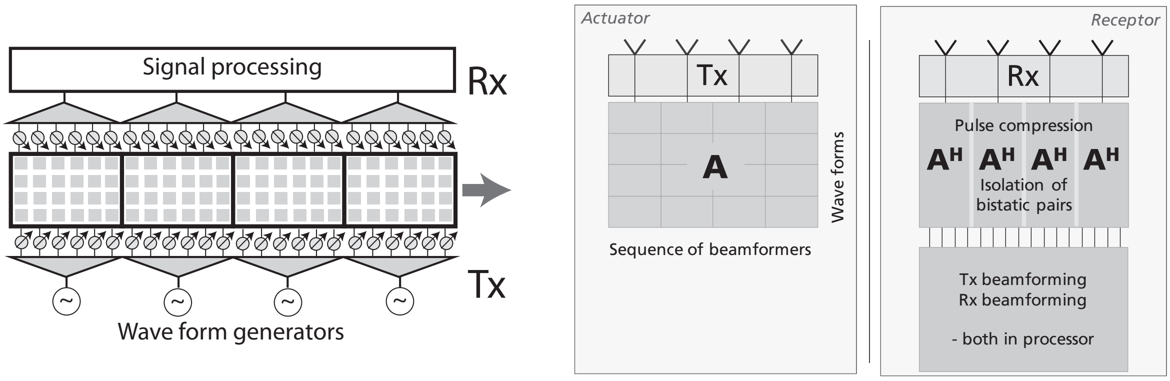


Figure 5: Left: Regarded type of MIMO antenna with N transmit and receive subapertures; Right: The MIMO operation permits the generation of signal vectors with N^2 spatial degrees of freedom

This means an only slight modification of the today commonly used phased array, but exhibits considerable enhancement of performance. The N waveforms fed into the transmit array now can be described by a matrix $\mathbf{A}$ with its columns assigned to the subapertures, see Fig. 5 right. On the other hand, the rows of this matrix represent a sequence of beamformers. It is obvious that the MIMO transmitter scatters the energy controlled and coded within the angular sector given by the mainbeam of the subapertures during the pulselength. For $\mathbf{A}^H\mathbf{A} = \mathbf{I}$ the MIMO receiver is able to decode the transmission channels and disassemble the Rx signals into the single bistatic paths from each Tx to each Rx element.

It follows the stage of signal processing opening the possibility for adaptive or not adaptive beamforming not only for the receiver but also for the transmitter. Within the subaperture beam e.g. narrow Tx-search beams can be formed or even multi-target tracking may be implemented - everything within the processor. Also for non-orthogonal codes the matrix $\mathbf{A}$ can serve as a model for excitation. For instance, pure phased array operation is obtained with columns identical up to scalar factors effecting Tx-beamforming. To cover the same angular sector as for the pure MIMO operation, the look direction has to be changed N times during the given time interval according to the transmit beam which is N times as narrow as the subaperture beam. By modifications of the matrix $\mathbf{A}$ it is also possible to combine subapertures and to perform MIMO with a smaller number of independent phase centers.

Thus the number of degrees of freedom is considerably increased due to the matrix stimulation. Nevertheless, the 'best choice' is depending on the situation, from the signal power, the distribution of clutter, the task (search, tracking) and of the number of illuminated targets. Moreover, what is the criterion to judge the performance? The signal-to-clutter-plus-noise ratio (SCNR)? The Fisher-information for parameter estimation? Other information measures as the information gain? ...

We can establish on the actuator side a *dictionary* of different waveform-ensembles $\mathbf{A}_1, \dots \mathbf{A}_K$

as a 'toolbox', see Fig. 6. It is the task of the *decider* to choose one of these ensembles for the next measurements.

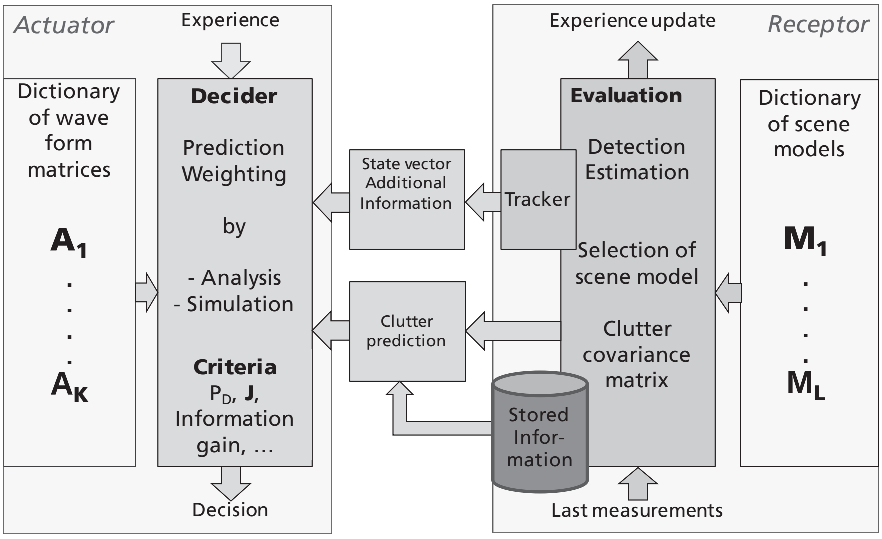


Figure 6: Perception-action cycle for phased array MIMO operation with a dictionary of modes

The decision depends on a state vector **S** from the perception side, which is built from measurements and stored information. If the system is e.g. in a tracking mode, the prediction of target parameters is an important source for the selection of an excitation matrix. The latter is e.g. a 'clutter-covariance map' gathered before or from former explorations of the same scene. On the perception side, there also may be a dictionary of typical scene properties to which the actual measurements are compared to find out the best fitting model.

For each of the K elements of the waveform dictionary, *reward maps* $P_{qk}, q = 1, \ldots, Q, k = 1, \ldots K$ according to the actual knowledge of the clutter covariance matrix distribution have to be calculated according to Q different performance measures, see Fig. 7. In our example the reward measures are evaluated in the direction - velocity plane. Depending on the task to be fulfilled (search, tracking, ...) a weighting is applied to the performance measures which are combined in a single accumulated reward map $\mathcal{P}_1, \ldots, \mathcal{P}_K$ per waveform. For each waveform this is integrated according to a certain a priori probability distribution p over this parameter plane. For tracking the latter can be based on the predicted state pdf, for search it will be a priority weighting. The result is the *reward* of the individual waveforms. Taking that waveform providing the maximum reward for the predicted state, the actuator i.e. the waveform generator will use this as the last step of 'cognitive MIMO radar'. Moreover, if the state transition dynamics are known, this 'greedy' decision policy can be further improved by the application of MDP (or POMDP) based approaches as described in chapter 3.

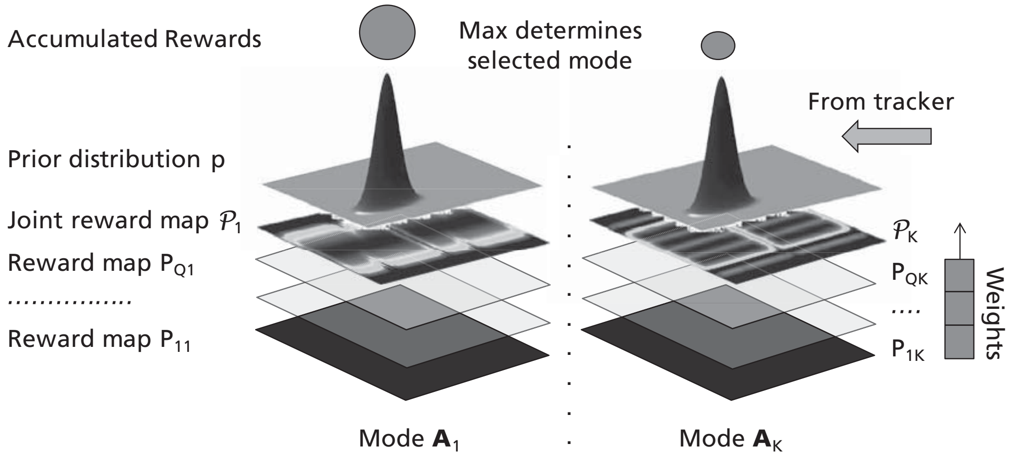


Figure 7: Selection of optimum mode based on the comparison of utilities distilled from utility maps

6. Outlook

Surely Simon Haykin's prophesies will become true up to a certain degree and cognition provides a basis for a new generation of radar systems with reliable and accurate capabilities which are still beyond the reach of traditional radar systems[1]. But - in our evaluation - the science of cognitive radar is still at the first beginning. Much time will be necessary to further develop the promising first approaches. Among the endless possibilities we have to find out those able to be realized with today's means and prove to attain considerable increase of performance in practise.

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Naval Radar Trends: A Look Back – A Look Forward

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Abstract: *The paper looks – chronologically spoken – back to the 90s of the last century, when the foundations were laid for a naval radar later to become the world market leader in the segment of small ship, air and sea target Surveillance and Target Acquisition Radar (STAR), named TRS-3D, developed and built by the former predecessor of Airbus Defence and Space, the TST Deutsche Aerospace. TRS-3D comprises a passive phased array antenna controlling its beam electronically in elevation and rotating electro-mechanically 360° in azimuth. At the beginning of the new century, the state of the art next generation TRS-4D emerged with four Active Electronically Scanned Array (AESA) apertures installed in a fixed way, two of them – now spatially spoken – covering fore and two of them covering aft of the ship, thus yielding an instantaneous full awareness around the platform. Additionally there is also a lower cost, rotating version of the TRS-4D, incorporating AESA capability. The paper finally gives a brief outlook on future developments of naval radar that can be expected.*

1. A Look Back

Over a period of nearly 20 years, the TRS-3D family of radar variants grew from a launching contract with the Royal Danish Navy to become the world market leader in the segment of small ship air and sea target Surveillance and Target Acquisition Radar (STAR), now having sold more than 60 systems worldwide and with a robust future ahead.

In the 1980s, the Danish Navy developed a new type of multi-purpose ship the size of a corvette, called the Stanflex-300 (SF-300) class. It has a length of 50 m, a quite low displacement of 450 t, and a maximum speed of about 30 knots (Fig. 1). The small platform size called for a compact radar with an extremely lightweight antenna.

In 1989 the Danish authorities issued a request for proposal for a multi-function radar for this platform with demanding requirements. TST Deutsche Aerospace proposed a 3D C-band Radar System capable of selecting different scanning patterns and modes of operation according to the immediate operational needs of the platform, quite a revolution at the time and seen mainly in then state of the art airborne radars.

Figure 1. Royal Danish Navy SF-300 with TRS-3D/16 on the mast-head

These modes included:

- A self-defence mode, combining short-range and high elevation scans with long-range scan-sectors within one antenna rotation period, for use in a rain, sea and ground clutter environment with a rotation time of 2 s
- A clutter mode for use in severe clutter conditions with a rotation time of 3.5 s
- A surveillance mode with 92 km instrumented range with a rotation time of 6 s
- A long range mode for use in ducting conditions, with 180 km instrumented range and a rotation time of 6 s

TRS-3D/16 is a fully coherent pulse-Doppler system, with simultaneous, complementary receiving and processing channels for ground targets, sea targets as well as for jammer detection and coherent sidelobe cancellation. The antenna utilises the same type of array as in the ground-based surveillance radar TRMS, but with a much smaller vertical aperture because only 16 rows are used. Operationally, the same flexibility in the use of different scanning patterns, polarisation agility, frequency and code agility is provided. The antenna for Coherent SideLobe Cancellation (CSLC) is integrated in the radar phased array. A planar IFF antenna with SLB is integrated below the radar antenna and below that, there is an additional antenna for a separate navigation X-band radar. The antenna group rotates mechanically in azimuth while the electronic elevation scan is performed, and is mounted on an electro-mechanically stabilized platform which compensates for pitch and roll movements (Fig. 2). The radar is capable of supporting Harpoon and NATO Sea Sparrow operations.

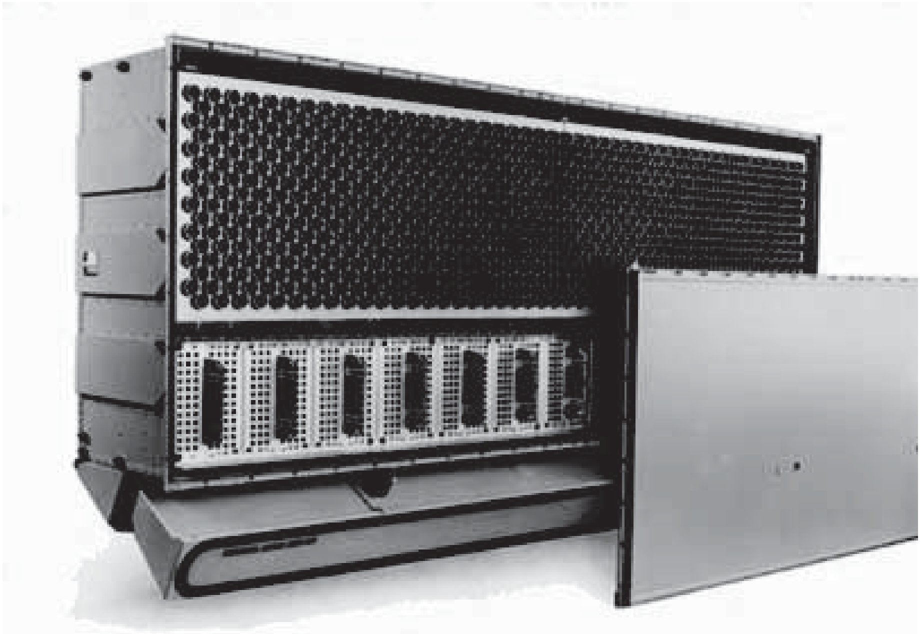

Figure 2. TRS-3D/16 Antenna Group

2. The Way Forward Towards TRS-4D via TRS-3D/16-ES

At the turn of the century, a thorough analysis of the worldwide operational needs of many potential naval customers was made and with a clear focus on best value for the operational customer, the TRS-3D family was placed on a solid product footing. TRS-3D/16-ES was born and the first ideas for what was to become TRS-4D were generated. The ES in the type designation refers to electronic stabilization of the antenna pattern for ship's pitch and roll, which eliminates the heavy and costly mechanical stabilization platform. TRS-3D/16-ES has the lightest top-weight in its class, allowing high-up installation on very small but potent ships, ensuring maximum operational benefits. The operating modes have been optimized for new threat scenarios. The limited value circular polarization was removed, but all other world-leading and unique operational features have remained and have been functionally improved over the years as computer processing technology has advanced.

TRS-3D/16-ES added a Gun Fire Support mode which allowed the direct support of medium calibre weapons against surface targets, such as the widely used Oto Melara 76 mm unit, without the need for a dedicated fire control radar. Firing trials have demonstrated unprecedented firing accuracy. In addition the radar has been interfaced to a variety of Surface-to-Air Missiles (SAM) on various platforms.

The TRS-3D product roadmap combined with batch production of TRS-3D/16-ES through to its current Baseline D has consequently exploited spiral development and insertion of state of the art technology. Additionally, exploiting the family approach in ground and naval radar, GaN technology from TRS-4D has been inserted into TRS-3D, replacing the TWT transmitter with a state of the art, high reliability, low life cycle cost, solid state transmitter.

TRS-3D/16-ES has been installed on a multitude of platforms across the world, including the National Security Cutter (NSC) class for the US Coast Guard's Deepwater programme and the US Navy's Littoral Combat Ship (LCS) class. Additionally, the land-based version of TRS-3D, the TRML-3D with modes optimized for Ground-Based Air Defence (GBADS), has been delivered to several customers around the world. An example of the TRS-3D installed base is depicted in Fig. 3.

Figure 3. TRS-3D Installed Base

3. A Look Forward: The Active Electronically Scanned Array (AESA) TRS-4D Radar

Since the beginning of the new century, the operational requirements faced by a naval warship have changed significantly. The potential theatre of war has moved from blue water to the littoral environment and in particular new asymmetric threats like FIAC's (Fast Inshore Attack Craft) have emerged. The threat and its direction are no longer that clear. Todays and future high-end warships like multi-purpose frigates are required to perform many different missions; for example, in addition to traditional Anti-Air-Warfare (AAW), Anti-Surface Warfare (ASuW) and Anti-Submarine-Warfare (ASW), they must also be able to operate in so-called low intensity scenarios like counter-piracy operations.

The increased propensity for operations in the littorals confronts the modern naval surveillance radar with several major challenges: an inhomogeneous, cluttered near-land environment and a wide range of targets with very low radar cross sections, such as extremely fast and highly manoeuvring anti-ship missiles, mini-UAVs or small high-speed surface targets. These targets have to be detected and tracked against a background of severe land and sea clutter, large ships with tens of thousands of square meters radar cross section, many birds, ground traffic, windmills and so forth. Of course, false alarms and false tracks should be kept to a minimum, but for suddenly appearing threat targets the critical time between first detection and the launch of a life-saving defence weapon has to be as short as possible.

On the other hand, the shrinking budgets of many navies are leading to a reduced number of warships and downsized crews. To make things even worse, the experience and skills of the crews are often decreasing too, so operation and maintenance of a modern, but at the same time high performance, naval surveillance radar has to be as simple as possible.

To address all these needs, CASSIDIAN (now Airbus Defence & Space) started the development of a new product family in addition to the well-known TRS-3D. As a prerequisite some new technologies had to be available.

GaN Technology: Compared to GaAs technology, the power level of GaN devices are 5 to 10 times higher and higher operating voltages can be used. This enables effective power amplification and TWTs can be cost-effectively replaced by solid-state transmitter amplifiers, in terms of acquisition cost but even more so in terms of life cycle cost.

AESA Technology and Digital Beam Forming (DBF): Active Electronically Scanned Arrays consist of many transmit and receive or combined Transmit/Receive Modules. Since the output phase and amplitude of each module can be controlled individually, beam steering in both dimensions (azimuth and elevation) can be done electronically nearly without any time lag. Digital beam forming, today possible due to the high processing power of state-of-the-art FPGAs, allows generation of the sophisticated receive beam patterns required to fulfil the different and partially conflicting requirements of a state of the art naval multi-function radar.

The use of these new technologies has enabled the implementation of some of the key features of the TRS-4D:

Multiple Beams on Receive, covering the complete elevation range, are digitally generated and processed in parallel (Fig. 4). In this way, the high dwell times are achieved which are necessary for accurate Doppler processing and very accurate elevation estimation. In addition, the receive beams can be stabilised electronically to compensate for the pitch and roll of the ship.

Figure 4. Multiple Beams on Receive