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.

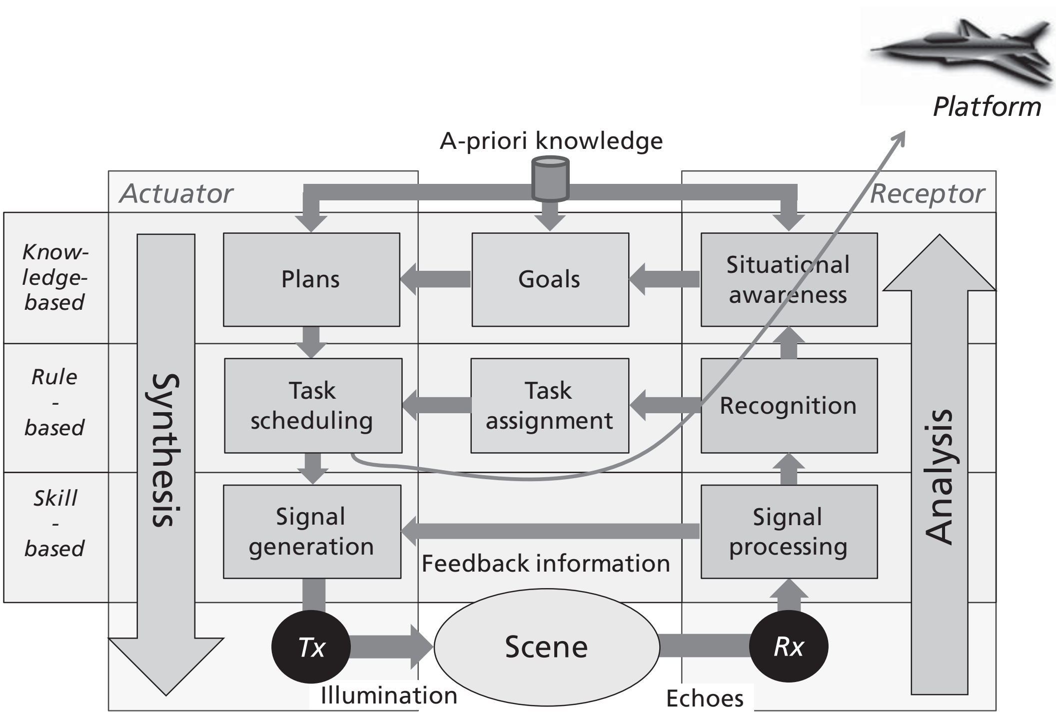


Figure 1: Three level model of cognitive radar deduced by the general model of Rasmussen

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.

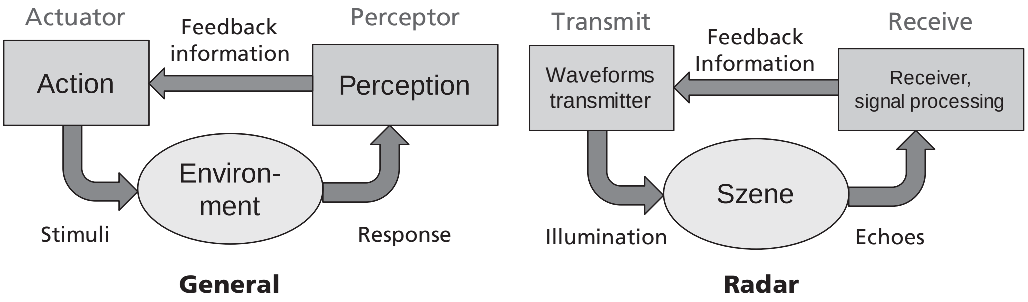


Figure 2: The perception - action cycle in general - also for human beings, and with respect to radar, see [1]

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

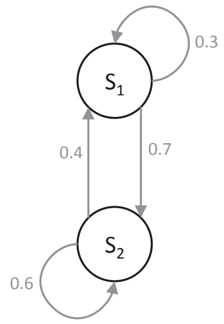
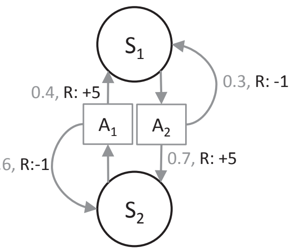
Markov Models		*Do we have control over the state transitions?*	
		No	Yes
Are the states completely observable?	Yes	***Markov Chain***	***Markov Decision Process (MDP)***
	No	***Hidden Markov Model (HMM)***	***Partially Observable Markov Decision Process (POMDP)***
Example of fully observable markov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

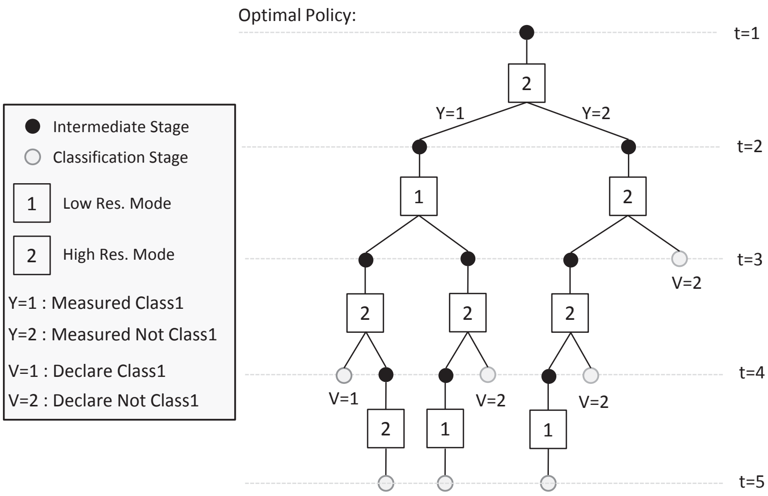
Even though this example could be augmented further by considering sensor mode resource consumption, it does indicate how the feedback mechanism of the perception-action cycle can increase the performance of typical radar tasks.

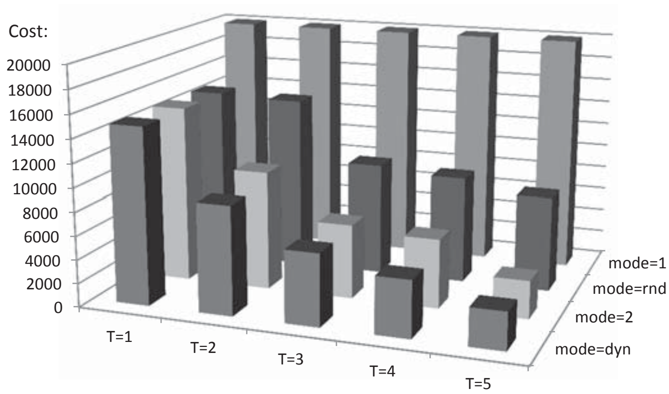
Confusion Matrix:

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.

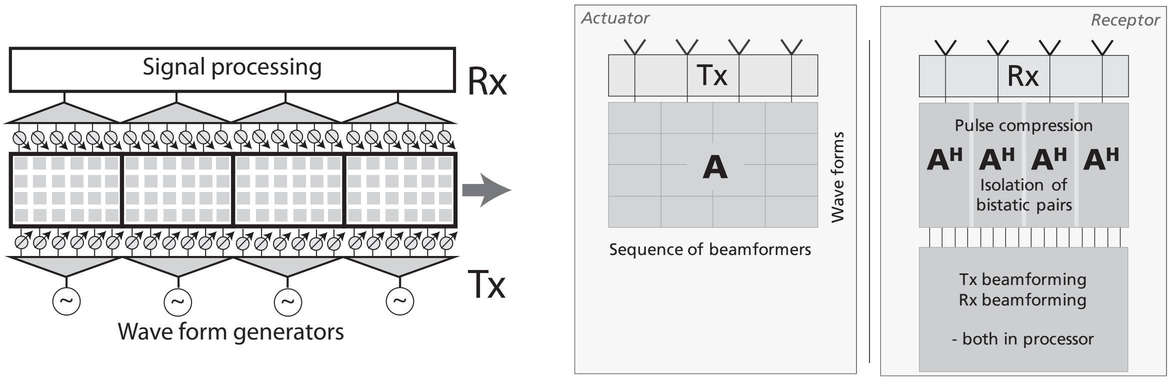


Figure 5: Left: Regarded type of MIMO antenna with N transmit and receive subapertures; Right: The MIMO operation permits the generation of signal vectors with N^2 spatial degrees of freedom

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 $\mathbf{A}_1, \ldots \mathbf{A}_K$

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

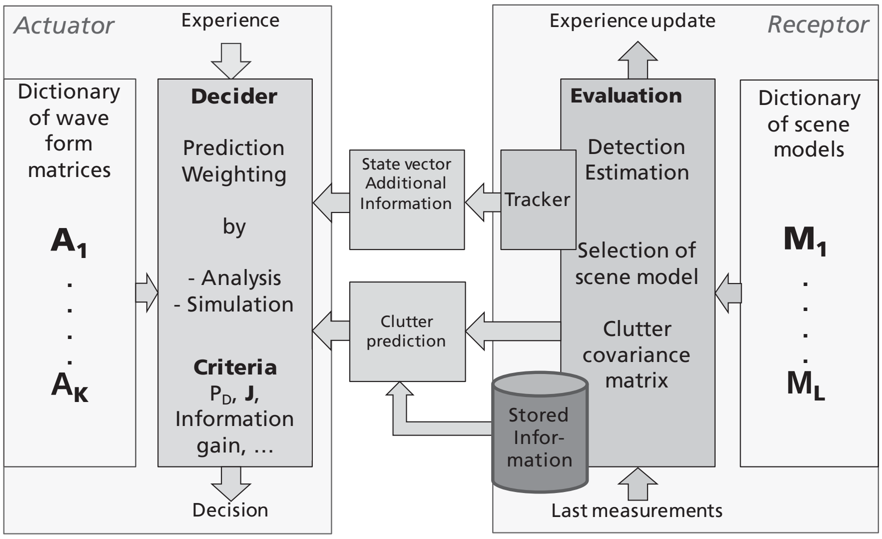


Figure 6: Perception-action cycle for phased array MIMO operation with a dictionary of modes

The decision depends on a state vector $\mathbf{S}$ 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.

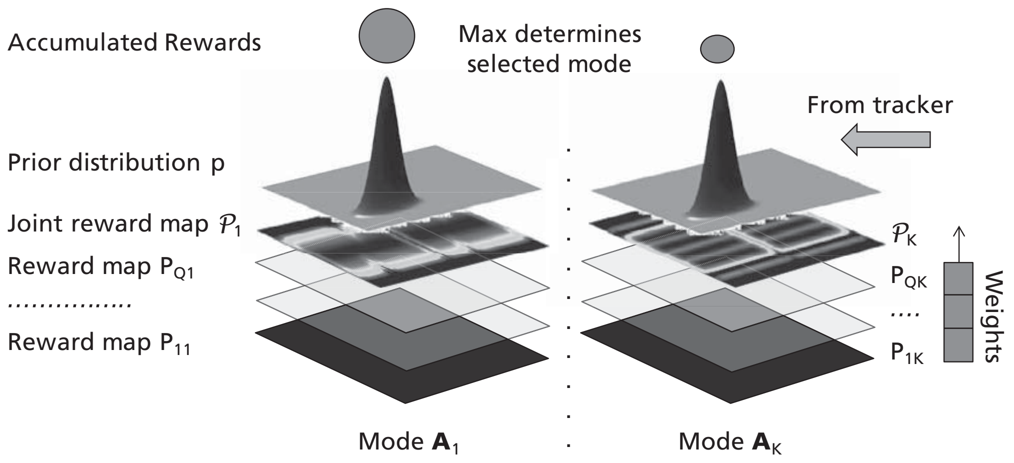


Figure 7: Selection of optimum mode based on the comparison of utilities distilled from utility maps

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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