An Introduction to Real-time Cognitive SONAR Systems Utilizing Novel MIMO Approaches

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Abstract

Cognitive systems have drawn the attention of researchers since several years. Different approaches have been proposed for RADAR, communication applications and recently also for SONAR systems. In contrast to a classical SONAR system the operator does not need to adjust the system parameters to account for changes in the environment or consider the potential type of the target (e.g. mammal, diver, submarine, etc.) to achieve an increased performance of the system regarding detection and tracking. Cognitive systems are capable to support a human being by essentially utilizing a feedback loop of the receive signal processing to the transmit signal processing. The cognition of the system can be achieved by a control unit which extracts the relevant information and adapts the parameters of the system. In this contribution a sketch of a system capable of real-time processing (i.e. following certain boundary conditions) is presented. In addition, the idea of MIMO (Multiple-Input-Multiple-Output) SONAR is shortly introduced and its application for cognitive systems is motivated.

Definition of Cognitive Systems

While cognitive systems have been initially proposed for RADAR signal processing [1] they have drawn little attention in SONAR research. Albeit the most sophisticated and specialized cognitive system available is utilized by the bat which senses its surroundings by an ultrasonic based echolocation approach [2]. Before presenting a possible application of the cognitive idea to a real-time capable SONAR system the definition and general idea of such a cognitive system is given.

As stated in the Oxford dictionary cognition is "The mental action or process of acquiring knowledge and understanding through thought, experience, and the senses." [3] Applying this definition to a technical system the senses are represented by sensors and experience by memory units. The act of thinking is described by all kind of predefined rules, cost functions and machine learning including the extraction of appropriate features with the goal of optimizing the outcome of certain tasks. Finally understanding is described by the connection of input signals utilizing the systems capability to "think" to its generation of output signals under consideration of gained experience. An imminent outcome of the knowledge of a system about its environment is the enhancement of a systems output. In case of *SONAR* the performance of the system, regarding detection and tracking is increased [1], [4].

SONAR Signal Processing

Although the latter proposed *Main Control Unit (MCU)* is until now just a sketch of possible connections between standard *SONAR* signal processing algorithms reinforced by machine learning as shown in Fig. 1, it will be seen that a high amount of flexibility of all applied algorithms is inevitable. Thus, the following components have been implemented to work with real-time capability at a standard desktop computer. To achieve this block-based and frequency selective processing of the different algorithms is carried out as described in [4].

Receive Signal Processing

First a flexible and robust filter-and-sum receive beamformer working at several frequency channels is implemented in the frequency domain to extract a two dimensional direction matrix (i.e. azimuth and elevation) per frequency band, hence the name multichannel. These results are now fed into a correlation module which performs a correlation for different target velocity hypothesis. Consequently utilizing characteristics of the transmit signals ambiguity function to suppress target reflections at velocities not fitting the hypothesis and thus improving the SNR and in common the output of the detector. At the basis of the previous processing a detection and tracking algorithm is carried out. In our system a multi-hypothesis tracker as supposed in [4] is currently implemented. For cognitive systems other approaches are supposed e.g. a Bayesian tracker, which inherits the detection and should have advantages over other algorithms due to neglecting hard decisions [1].

Transmit Signal Processing

Transmit signal processing consists mainly of a very flexible signal generation module which is capable of generating a variety of different waveforms like CW (Continuous Wave), LFM (Linear Frequency Modulation), CUT-FM (Cutted-FM), Pseudo-Noise to be able to select due to this catalogue optimal waveform for a certain scenario and improve the SNR (Signal-to-Noise-Ratio) or SRR (Signal-to-Reverberation-Ratio). In addition nature could be mimmiced, namely the behaviour of *constant frequency echolocation bats* [5] and the transmit signal altered in such a way that the input signals frequency range including Doppler shifts (due to own and target movement) fits the most sensitive area of the underlying hardware. Afterwards a transmit beamforming is carried out again utilizing a robust filter-and-sum approach.

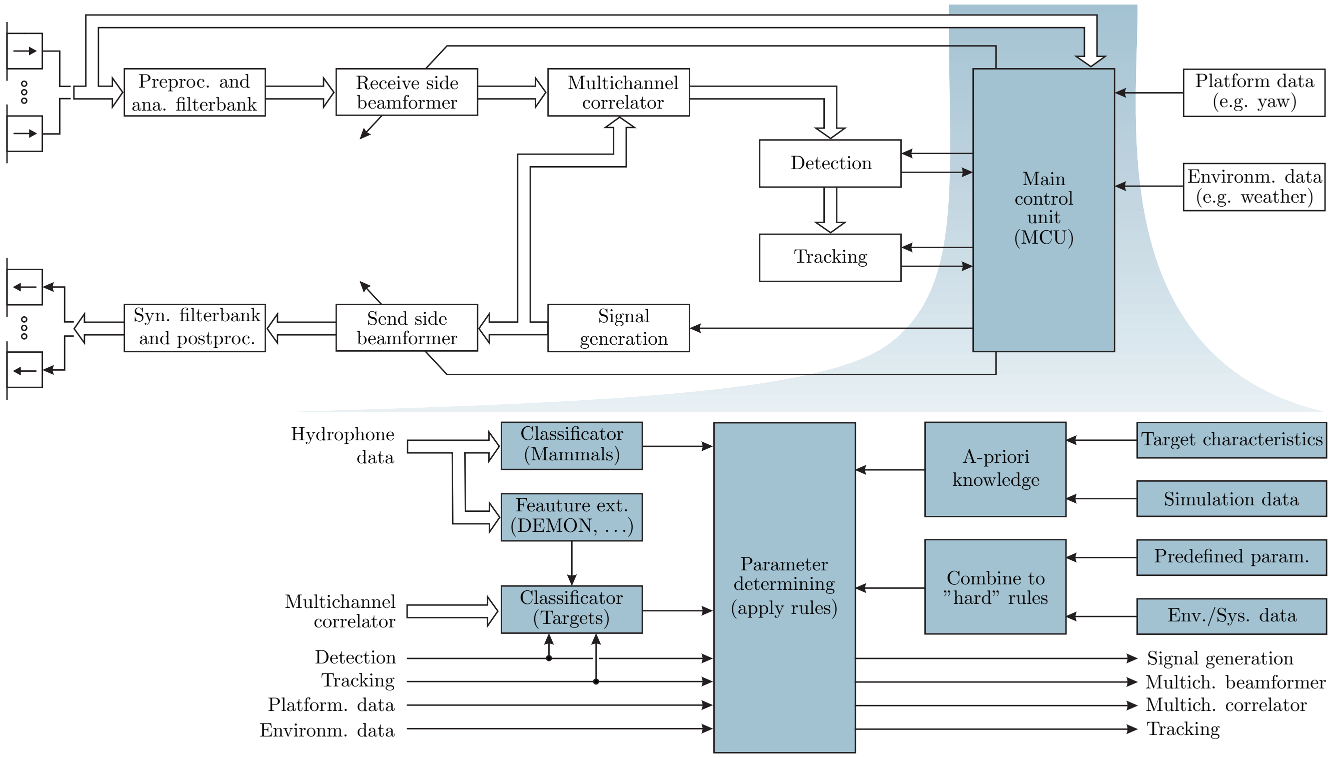

Figure 1: *SONAR* signal processing chain, blue components added for cognitive capability. *Upper part:* General signal processing chain. *Lower part:* Sketch of a possible *Main Control Unit (MCU)* fitted in the signal processing chain.

Sketch of a Main Control Unit

In case of a cognitive *SONAR* system the acquisition of raw data is presented by a multiple of sensors recording relevant information e.g. temperature, wind speed, salinity, platform movement, speed and acceleration. From this input datastream relevant features and information are finally extracted with the goal of an automatic classification of the situation including possible targets. Some possible features including their purpose are presented in the following:

- *DEMON* (Detection Envelope Modulation On Noise) or *LOFAR* (Low Frequency Analysis and Recording) analysis [6] for classification of ship classes. An appropriate training database is mandatory. This knowledge can in advance be linked e.g. to a catalogue of possible speed ranges, target extents and reflection coefficients to get a better validation for the latter tracking algorithm.

- Additional features to be extracted would be speed estimates using Doppler analysis [7] and knowledge about the targets extent gained by the number of range cells occupied.

- In addition some kind of marine mammal classificator [8] linked to a passive *SONAR* mode could be used analogical to the processing mentioned before.

The connection of the detector findings with the output of the classifiers is now used to improve the tracker results due to a-priori knowledge, e.g. by predicting possible speed ranges of the target which are describing a possible movement area. Thus, false tracks could be decreased. Haykin refers to this part of the systems cognition as equivalent to *short-term memory*. In addition to this, a cognitive system needs to prioritize certain tasks over others. This gets clear when looking at a situation with more than one possible approaching target. Assuming now that one target would be a dolphin the other an enemy diver and the third a buoy. A human would intuetively priorize the systems processing time for each target based on experience. A computer-system would allocate equal time slots if no additional rules are defined. This leads to a decreased resolution of the target movement in time and such could lead to dangerous situations. An obvious solution is the classification of target groups to *thread level*. Each *thread level* is *(1)* connected to a certain radius (*sensitivity border*) and *(2)* to the radial velocity towards the platform. If this border is violated and the target is moving towards the system it concentrates more of its available processing power (i.e. time and energy) in illuminating and following this target (see Fig. 2). Not classified targets are per default connected with the outmost defined *sensitivity border*. Utilizing a-priori knowledge about the environment e.g. sea surface maps, sound speed (or temperature plus salinity) and depth profiles under the premise of continuously defining the own position the in [9] proposed real-time capable ray-tracing algorithm could be used to farther increase the accuracy of the system. Utilizing this approach leads to less erroneous calculation of distances based on bend paths (rather than the assumption of a direct propagation of the rays). Due to this the accuracy of ranging is increased. In addition, occurring ghost targets due to multipath propagation could be recognized, filtered out and, as a consequence, false alarms significantly reduced.

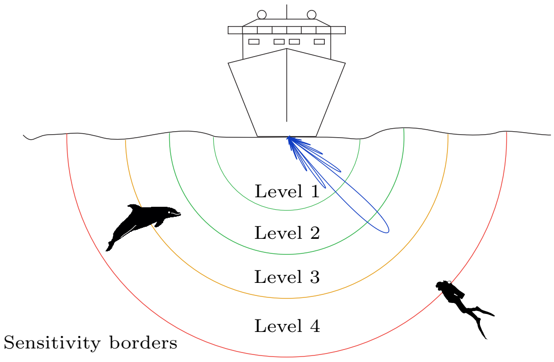

Figure 2: Illustration of *sensitivity borders* for two approaching targets.

A sketch on how the *MCU* could be integrated is shown in Fig. 1.

Exemplaric Cognitive Setup

As a generic implementation of such a system is very complex a simplified approach selecting from a predefined set of operating modes and alternating parameters by simple rules is presented in the following. Choosing this approach algorithms can be tested in sense of adaptability and the general impact of a cognitive system examined. Again nature can be mimed which results in an adaptation of some signal generation parameters according to the behaviour of bats while chasing prey [10]. This leads to the following exemplaric relation between environmental sensing (ES) and parameter adaptation (PA):

- Target distance *decreasing* [ES],
- Pulse repetition frequency *increasing* [PA],
- Pulse duration *decreasing* [PA],

A more detailed solution for adaptation of some selected parameters under consideration of the possibility of multiple targets can be calculated as follows. The time dependend target range ($R_{Tar}(n)$) is calculated by:

$$R_{Tar}(n) = \max_{l \in L(n)} \{D_{Tar,l}(n)\}, \tag{1}$$

with target distance $D_{Tar,l}(n)$ for target l and the number of detections $L(n)$. The max. observable range ($R_{obs,max}(n)$), i.e. detection range, is defined by:

$$R_{obs,max}(n) = R_{Tar}(n) + O_F, \tag{2}$$

where O_F is a predefined offset. $R_{obs,max}(n)$ is bounded by the performance of the system. The lower limit for ranging is:

$$R_{obs,min}(n) = d_p(n)c_w, \tag{3}$$

with variable pulse duration $d_p(n)$ and sound velocity c_w. The highest ping repitition interval (PRI) for detecting targets in $R_{obs,max}$ is described by:

$$T_{PRI}(n) = \frac{2R_{obs,max}(n)}{c_w}. \tag{4}$$

Such equations are included in the *MCU* as rules and should lead to faster and less erroneous tracking. As stated in [10] bats utilize three different operating modes, namely *search*, *approach*, *terminal*mode. An equivalent to the *search* mode will be refered to as *scan mode* in the following. This mode presents a general omnidirectional search for possible targets. The detector is parametrized to be very sensitive. Such missed tracks are decreased but false detections are increased. An equivalent to the bats *approach*-phase is referred to as *potential target mode*. This mode is used to verify possible targets found in the *scan mode*. For each target (beam) the detectors sensitivity is controlled individually and gets gradually decreased. As a third mode the active *SONAR* gets extended by a passive mode (referred to as *sensing mode*) which permits the system utilizing the previously mentioned classification techniques like *DEMON*. The parameter determination gets further refined by utilizing the previously introduced *sensitivity borders* to build a pattern for switching between the possible operating modes. An example is depicted in Fig. 3. The value for *max successive pings* depends on the current *thread level* connected with the investigated target.

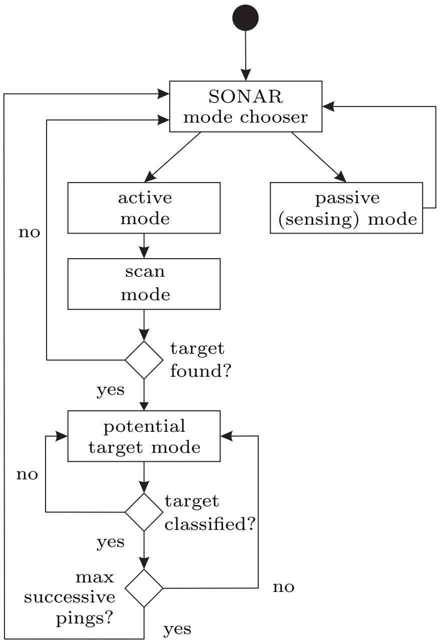

Figure 3: State diagram - Changes between predefined general operating modes based on events occuring due to environmental sensing.

Adding flexibility using MIMO processing

As mentioned before high parameterizable algorithms are inevitable. This motivates the application of *MIMO* techniques in cognitive systems. In the following a monostatic setup and uniform linear arrays for the transmit and receive hydrophones are assumed. In general there are two possible realizations:

Multibeam-MIMO (MB-MIMO)

The *MB-MIMO* utilizes mutual orthogonal waveforms to form independent beams. Each of the waveforms is transmitted by each transducer. Thus independent transmit beamforming is possible which implies a simultaneous

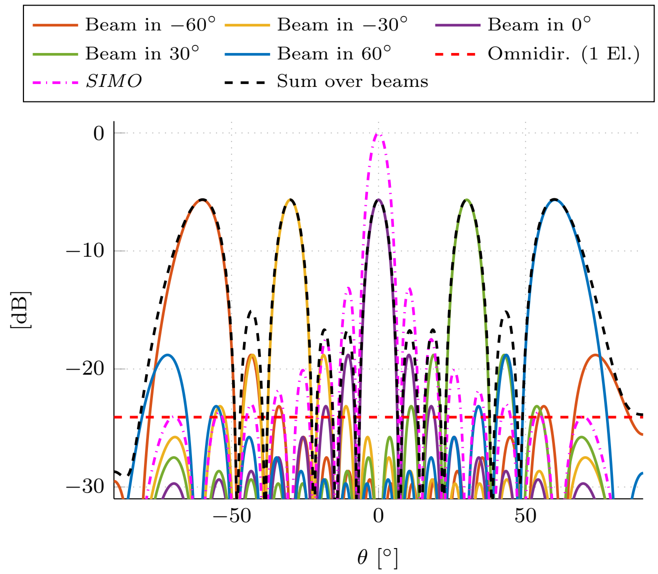

Figure 4: *MB-MIMO* individual beams for equal number of transmit/receive elements($N_{\mathrm{Tx}} = N_{\mathrm{Rx}} = 16$), equal inter-element spacing ($d_{\mathrm{Tx}} = d_{\mathrm{Rx}} = \lambda/2$) and 5 transmit beams.

tracking of multiple targets or in case of doppler sensitive processing multiple velocity hypotheses. Thus an application in the previously introduced *potential target mode* is usefull as it makes a parallel tracking of serveral targets possible while increasing the *SNR* over omnidirectial transmission. A drawback using this approach over a classical *SIMO* technique is the decreased power for each beam (cf. Fig. 4) if a maximum transmission energy for each transducer is assumed.

Virtual-aperture-MIMO (VA-MIMO)

Again mutual orthogonal waveforms are used. In difference to the *MB-MIMO* just one waveform per transducer is send. As a consequence there will be no coherent overlapping and thus no transmit beam is formed. The sum of all transmit waveforms is finally recorded by each of the receive elements. Now matched filtering will be applied for all receive elements and transmit signals and thus a total number of $N_{\mathrm{Tx}}N_{\mathrm{Rx}}$ signals extracted. Now beamforming can be applied for a total number of $N_{\mathrm{Tx}}N_{\mathrm{Rx}}$ virtual elements, hence the name *virtual-aperture*. A higher number of elements leads to an increased resolution (cf. Fig. 5). A more detailed explanation including the necessary maths can be found e.g. in [11] or [12]. One application area of *VA-MIMO* is a refined *scan mode*. The orthogonal (omnidirectional transmitted) waveforms could account different target reflection characteristics or velocity hypothesis and thus improve the systems outcome. In addition this technique leads to the capability of offline transmit and receive beamforming.

Outlook

This contribution showed a short summary of possible cognitive *SONAR* techniques. The next steps towards such a system is the development of new flexible algorithms to reinforce the cogntive idea. *MIMO* techniques in general should be mentioned as a promising approach.

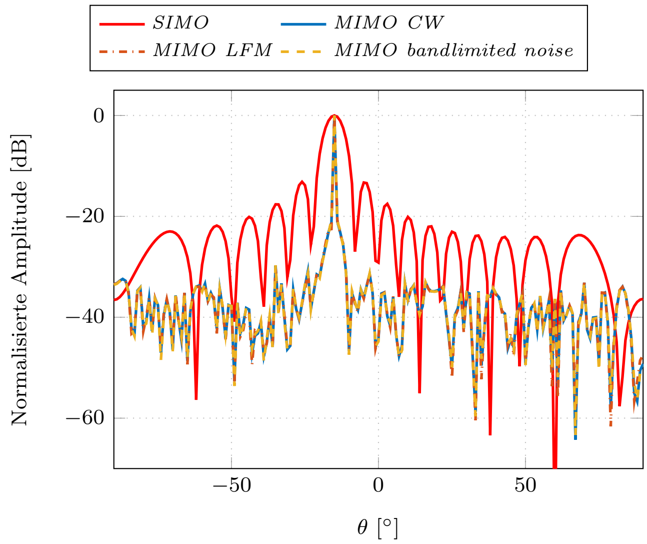

Figure 5: *VA-MIMO* beampattern for different transmit signals for $N_{\mathrm{Tx}} = N_{\mathrm{Rx}} = 16$, inter-element spacing $d_{\mathrm{Tx}} = N_{\mathrm{Rx}}d_{\mathrm{Rx}} = N_{\mathrm{Rx}}\lambda/2$. *SIMO* beampattern for $N_{\mathrm{Tx}} = N_{\mathrm{Rx}} = 16$ and $d_{\mathrm{Tx}} = d_{\mathrm{Rx}} = \lambda/2$.

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