A Real-time MIMO System for Sonar Applications

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Introduction

Active sonar systems for target detection and tracking have been intensely studied over the past decades and focused the attention of many researchers worldwide. The basic principle of an active sonar system thereby never changed: emitting a sound pulse (ping) and listening for the echos to gather information of the underwater environment [1]. This simple principle is, however, challenging due to limited bandwidth, extended multi-path, refractive properties of the medium, severe fading, rapid time-variation of the channel, and large Doppler shifts [2].

There are numerous parameters which need to be considered to gain optimal sonar-system performance. In addition, the optimal configuration of these parameters is highly depending on the application of choice (e. g., either diver detection or anti-submarine warfare). This requires on the one hand, the use of an optimal hardware for transmitting the pulse and receiving the echo and, on the other hand, a signal processing that leads to a robust target detection. In this contribution a so called *"cognitive-"*sonar signal processing is proposed that is able to work in real-time. Additionally, first results of the system's behaviour within a simulated environment are shown.

Main principle

In traditional active sonar systems, the sonar designers take little account of the influence of the environmental information and prior knowledge perceived by a sonar receiver [3]. The behavior of the sonar system is kind of stiff. This is not optimal, considering the complicated transmission characteristics of a fast changing underwater channel. Here applies the idea of cognitive sonar. According to the *Oxford English Dictionary,* cognition is "knowing, perceiving, or conceiving as an act". This quotation illustrates the capabilities of a cognitive sonar system by focussing on three main points:

- knowing: sensing the underwater environment,
- perceiving: process the data, extract information and learn through interactions of the sonar with the environment,
- conceiving: optimize the transmit signal for target detection based on the gained information, through feedback from the receiver to the transmitter.

In this paper, we follow one simple principle, illustrated in Fig. 1: The traditional signal processing A on the left side produces an output for a tracking module which gives the result 1. On the right side, we consider a signal processing B which is optimally tailored to individual

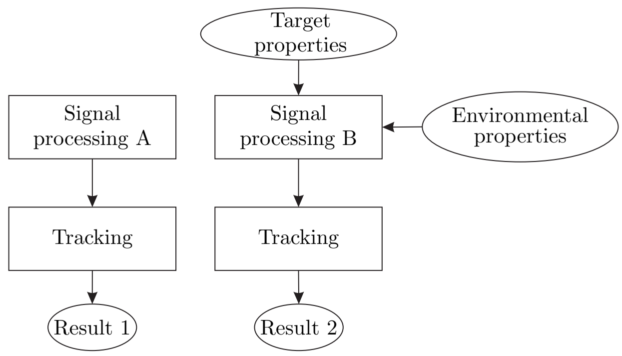

Figure 1: Main principle of the target detection of a traditional sonar signal processing (left) compared to the cognitive approach (right) followed in this paper. The result 2 is at least equal or better than result 1, e. g., in terms of track probability of detection or track false-alarm rate [4].

target and specific environmental properties. It is obvious that the output of signal processing B produces, after the tracking block, the result 2 being equal or better than result 1, e. g., in terms of track probability of detection or track false-alarm rate [4], since it makes use of extra information. So the main idea is to add a certain intelligence to a sonar system. However, the challenging part of this approach consists of four main points:

1. The optimal measuring of the target and environmental properties.
2. The optimal utilization of the measured parameters within the signal processing.
3. The highly time-variant environmental and target properties.
4. The existence of multiple targets.

Based on the development of cognitive radio [5], Haykin proposed in 2005 a cognitive radar [6]. In the following years this concept attracted reasonable attention in the field of radar applications which emphasized different aspects of cognition [7, 8].

Haykin describes in [5] the echo-location system of bats as a physical proof of an optimal cognitive localization system. Bats emit ultrasonic sound pulses that can vary in frequency, amplitude, and pulse-repetition rate.

Proposal

In this paper we propose a cognitive sonar system that shows several analogies to the localization system of a bat. It utilizes information form the environment to improve target detection, but emphasizes, compared to known cognitive sonar systems from the literature, on

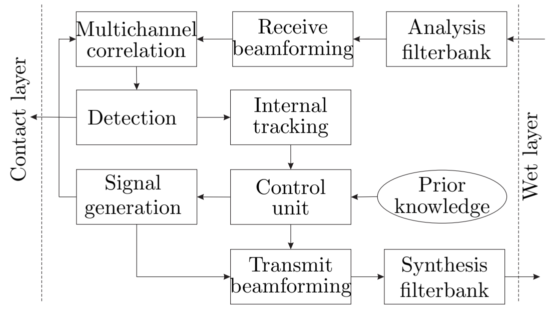

Figure 2: Schematic of the signal processing for a cognitive sonar system.

target-specific parameters. The system is able to work in real-time on a personal computer (PC) and continuously adapts its receive and transmit signal processing to its ever changing environment and specific target properties. There are two ways the system is able to perform these cognitive adjustments:

1. Change the transmit signal.
2. Change the direction of the transmit pulse.

The information on which these changes depend are obtained by means of an internal tracking system. When unsecure tracks occur, the system tries to prove or disprove them by optimizing subsequent pings. This is done using the information fed back from the tracking algorithm and applying external information[1]. The central part of the signal processing unit that is capable to handle this information, is a matched filter and its corresponding Doppler processing that enables a flexible signal analysis.

The cognitive sonar system

Technical boundary conditions

The proposed signal processing for the cognitive sonar system is designed to work in a real environment in real-time. Therefore, certain hardware restrictions, acting as boundary conditions for the proposed system, need to be considered in the signal processing.

The used receiver consists of 48 channels (so called "staves"). The transmitter (projector) consists of 32 channels. The system is able to directly access each stave individually. Hence it is possible to generate arbitrary waveformes for each stave which enables the possibility for transmit beamforming. The resonance frequency lies between 50-80 kHz and the system works at a sample rate of 192 kHz. Despite the fact that hydrophone and projector are physically separated, the system is designed to work in a mono-static behaviour. The signal processing is capable to work on a standard PC.

System implementation

The structure of the proposed cognitive sonar system is shown in Fig. 2. In order to achieve a sufficient real-time performance, extensive frequency-domain processing is used, and the signal processing is executed in small blocks, so called frames[2]. After one frame on each channel of the hydrophone is received[3], the block is transformed via an analysis filterbank into the frequency domain. This is followed by a receive-beamforming module that forms a direction matrix. The beamforming module is implemented as a fixed filter-and-sum beamformer which utilizes a Hann window[9]. Due to the fact that bandlimited signals are used, it is possible to save processing load by applying the computation only in the relevant frequency range. This principle is further called "frequency-selective estimation".

The direction matrix is "matched-filtered" using a cross-correlation module, which is able to correlate the incoming signal with several stretched or compressed versions of the transmitted signal in parallel.

The correlation matrix is processed in a detection module, consisting of two components: a constant-false-alarm-rate (CFAR) detector with range-dependent threshold [10] and an associated connected-component-analysis (CCA). It is possible to chose between three CFAR-methods: *cell-averaging-, cell-averaging-greatest-of-,* and *cell-averaging-least-of-*CFAR. The CCA estimates the size and the centroid of a detected object and generates a contact. This contact data is passed, on the one hand, to the outside world[4] and, on the other hand, to an internal tracking module. It is to be noted that, when referring to the tracker in the following, the internal tracking module is always meant.

The implemented tracking module uses a Multi-Hypothesis tracker (MHT) based on [11]. This MHT system is a single-target tracker, suitable in case of missing detections and false alarms [12], but it also works for multi-target scenarios, if the targets are well separated [13].

Based on the tracked data, a control unit adds a certain "intelligence" to the system. It decides which transmitted signal is generated and controls the beampattern of the transmit beamformer. After synthesis, the generated signal is transmitted through the projector.

The system initially needs to scan its surrounding in a broad manner. For the sake of simplicity, this mode is further called "scan mode". The scan mode uses Doppler-invariant signals, e. g., frequency-modulated (FM) signals. When the tracker detects a potential target in scan mode, the control unit is able to switch to an "adaptive mode" in which target properties are considered and optimized waveforms can be applied. The choice of the targets for which the signal processing is optimized, depends on the targets' track quality. To quantify the quality of the tracks, the tracker utilizes a method called "Sequential Track Extraction" [14] that outputs a track score. If the track score is high, it is not necessary to

[1]The external information is given by the user or a device and can include various informations, e. g., water depth or positions of stationary clutter.

[2]Typical frame sizes ranges between 64 and 512 samples.

[3]Indicated as wet layer in Fig. 2.

[4]Stated as contact layer in Fig. 2, e. g., an external tracking system.

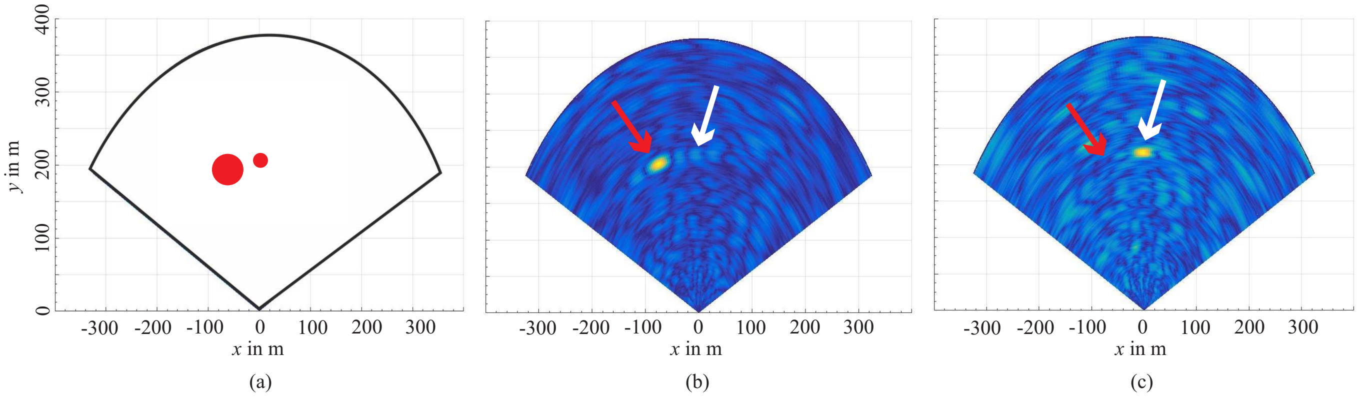

Figure 3: Output of the Cognitive MIMO sonar system for a simulation with one big object and one small target (a). The correlation output in scan mode (b) and adaptive mode (c) is shown. In adaptive mode, the transmit beamformer blocks the emission of sound in the direction of the big object.

adapt the waveform, if the track score is low, there are two main possibilities:

1. There is no real track but the obtained track stems from false alarms.
2. There is a real track but the measurement method is not optimal.

In both cases, the adaptive processing can help to improve the result by applying an optimized waveform. This leads either to discard the track, or it helps to raise the track score.

This behavior can be supported by a transmit beamformer that blocks the transmission of the pulse into the direction of an interferer. In the current implementation of the system, the control of the blocking beamformer is carried out from outside, e. g., the user who has a-priori knowledge. In a future implementation, the control of the beampatttern can automatically be controlled based on tracking data through the control unit.

Using target-specific transmit signals and transmit beamforming patterns leads to the drawback of getting blind for the major environment except for particular targets. Therefore it is important to switch the adapt mode and the scan mode with a regular heuristic. In the current implementation, the system is alternating between the two modes. This can be improved by individual transmit patterns. It is possible to adjust the inter-ping interval individually depending on the targets' distance. This can increase the pulse repetition rate and thus optimize the information flow per time.

Simulation results

In this section, the system behavior is shown for two particular simulations, to show the potential of the adaptive signal processing. The first simulation emphasizes on the advantage of using a transmit beamformer in adaptive mode. The second simulation shows the ability of the system to adapt the transmit signal to specific target velocities.

Figs. 3 and 4 are showing the results of the two simulations. In both figures, the transmitter and the receiver are located at the origin of the coordinates and the system is looking forward in y-coordinate direction with a fan width of 120 degrees. Figs. 3 (a) and 4 (a), respectively, depict the location of certain objects in the particular simulative situation. Figs. 3 and 4 (b) and (c) show the output of the correlator module for the given situation.

In the first simulation, two objects are located in a noisy environment (see Fig. 3 (a)). One big unwanted object (left) with a relative high target strength and a small target (right) with a relative low target strength are placed close to each other. The system is initially situated in scan mode, where a CW-transmit signal is used and the pulse is transmitted omni-directionally. In Fig. 3 (b) the big object is clearly visible at the correlation output (red arrow). The small target is hidden within the grating lobes of the receive beamformer resulting from the big object (white arrow). The detection algorithm thus is not able to detect the target.

With prior knowledge (e. g., sea maps, sonar operator or observation) the system is able to change the transmit beampattern in adaptive mode. The transmit beamformer blocks the transmission of the signal in the direction of the big object. The result is shown in Fig. 3 (c). The target is clearly visible (white arrow) while the backscattering strength of the big object is reduced (red arrow). Hence the detection of the small target is possible.

In the second simulation, three items are located in a cluttered, noisy environment (see Fig. 4 (a)). One small target with a relatively low target strength is moving at a radial speed of 8 m/s . Two big targets, with a relatively high target strength, are moving at a different speed. In scan mode, the system uses an FM signal with an omni-directional transmit beampattern. The result of the correlation module is shown in Fig. 4 (b). The detectability of the two big targest results in a high track score of the tracker(red squares). The small target (red arrow), is also tracked but results in a low track score due to its low detectability. The system tries to raise the

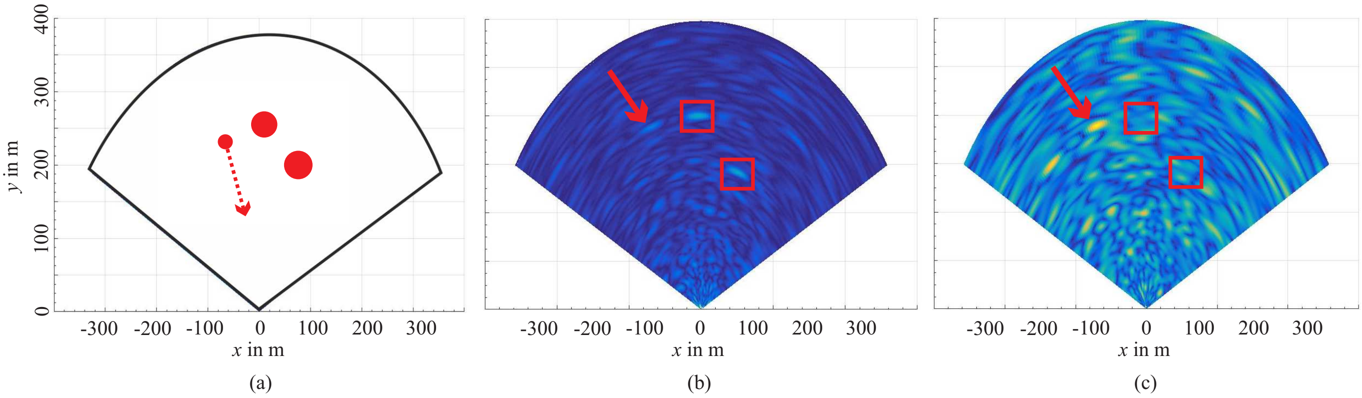

Figure 4: Output of the Cognitive MIMO sonar system for a simulation with three targets (a). The correlation output in scan mode (b) and adaptive mode (c) is shown. In adaptive mode, a Doppler processed correlation, tailored on the small target velocity, is used.

detectability by switching into adaptive mode and hence to improve the track score. In Fig. 4 (c) the correlation output of the adaptive mode is shown. The system now uses a Doppler sensitive CW pulse, and the direction matrix now is correlated with a Doppler-processed version of the transmit pulse. It can be seen that the stationary clutter and the two big targets are not visible anymore (red squares) while the small target is clearly seen (red arrow).

Conclusion and Outlook

In this contribution, the principle of a cognitive sonar system was shown and the implementation of a real-time cognitive MIMO sonar system was proposed. Simulation results show that the high amount of flexibility enables the system to enhance the target detection through using adaptive signal processing. Further investigations are necessary to improve the system and to prove this concept in a real-life environment.

References

[1] A. D. Waite, *Sonar for Practising Engineers*. Wiley, 2001.

[2] M. Chitre, S. Shahabudeen, L. Freitag, and M. Stojanovic, "Recent Advances in Underwater Acoustic Communications and Networking," in *OCEANS 2008*, Sept 2008, pp. 1–10.

[3] L. Xiaohua, L. Yaan, L. Guancheng, and Y. Jing, "Research of the Principle of Cognitive Sonar and Beamforming Simulation Analysis," in *Signal Processing, Communications and Computing (ICSPCC), 2011 IEEE International Conference on*, Sept 2011, pp. 1–5.

[4] S. Coraluppi, D. Grimmett, and P. de Theije, "Benchmark Evaluation of Multistatic Trackers," in *Information Fusion, 2006 9th International Conference on*, July 2006, pp. 1–7.

[5] S. Haykin, "Cognitive Radio: Brain-Empowered Wireless Communications," *Selected Areas in Communications, IEEE Journal on*, vol. 23, no. 2, pp. 201–220, Feb 2005.

[6] Haykin, "Cognitive Radar: a Way of the Future," *Signal Processing Magazine, IEEE*, vol. 23, no. 1, pp. 30–40, Jan 2006.

[7] S. Haykin, Y. Xue, and P. Setoodeh, "Cognitive Radar: Step Toward Bridging the Gap Between Neuroscience and Engineering," *Proceedings of the IEEE*, vol. 100, no. 11, pp. 3102–3130, Nov 2012.

[8] L. Fan, J. Wang, D. Shu, and B. Wang, "Time Allocation in Cognitive Radar for Multitarget Detection with Dynamic Programming," in *Control and Decision Conference (CCDC), 2010 Chinese*, May 2010, pp. 839–842.

[9] H. van Trees, *Detection, Estimation, and Modulation Theory, Optimum Array Processing*. Wiley-Interscience, 2002.

[10] V. D. Nguyen, "Small-Target Radar Detection and Tracking within the Pitas Hard-and Software Environment," in *Future Security*, 2012, pp. 347–358.

[11] W. Koch, J. Koller, and M. Ulmke, "Ground Target Tracking and Road Map Extraction," *ISPRS Journal of Photogrammetry & Remote Sensing*, vol. 61, no. 3–4, pp. 197–208, 2006.

[12] V. D. Nguyen and T. Claussen, "Individual-gating-by-sorting in MHT," in *Information Fusion (FUSION), 2014 17th International Conference on*, July 2014, pp. 1–8.

[13] M. Daun and F. Ehlers, "Tracking Algorithms for Multistatic Sonar Systems," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, pp. 35:1–35:28, Feb. 2010.

[14] G. van Keuk, "Sequential Track Extraction," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. 34, no. 4, pp. 1135–1148, Oct 1998.