A Real-time Cognitive-Sonar System for Diver Detection

Tim Claussen, Viet Duc Nguyen, Ulrich Heute, Gerhard Schmidt
Digital Signal Processing and System Theory
University of Kiel
Kiel, Germany +49 431 880–6144
Email: tic@tf.uni-kiel.de
Fax: +49 431 880–6128

***Abstract*—Cognitive signal processing has been intensively studied over the past years. Nevertheless, cognitive sonar systems only draw little attention in the research community. In this paper the signal processing of a cognitive sonar system for diver detection is shown in detail. It is inspired by the target-detection system of a bat and thus able to adapt its signal processing units to measured parameters of particular targets. This is done by adjusting the transmitted signal as well as the direction of the transmitted energy of the active sonar system by transmit beamforming. Thereby, it is possible to improve on the one hand the probability of detection of a target for a given signal-to-noise ratio (SNR) as well as signal-to-reverberation ratio (SRR) and, on the other hand, to extend the spatial awareness by adapting the transmit beamformer. This technique leads to a combination of two spatial filters: the receive beampattern and the transmit beampattern. To obtain target-specific parameters, the data form an internal tracking system is used. After showing a general system overview, the core parts of the signal processing are shown in detail. At this point we focus on the Doppler processing with its real-time interpolation and correlation algorithms. Monte-Carlo simulations illustrate the potential of the proposed system by comparing the results with conventional active-sonar signal processing.**

I. Introduction

Active-sonar systems for the surveillance and the security of ships, harbors, and coastal areas are essential for offering protection against attacks of divers. The basic principle thereby never changed: transmitting an acoustic pulse (ping) and interpreting the echos to identify potential targets. However, this is a challenging task for a sonar system: Besides a noisy surrounding, the environment is usually reverberation-dominated due to the numerous backscattering objects and boundaries like harbor walls, boat hulls, the seabed, or the surface of the water [1]. The target strength of the background often resembles the target strength of a diver, so the difficult part is to distinguish between a diver and unwanted objects. The sound-propagation properties of water are not optimal due to their limited bandwidth, extended multi-path, and refractive properties as well as severe fading, and rapid time-variation of a channel with large Doppler shifts [2]. Therefore, a suitable signal processing is mandatory.

Hence, active-sonar systems for the detection and the tracking of small targets like divers draw the attention of many researchers worldwide which leads to a well-founded signal processing knowledge in this research area. Nevertheless, 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]. At this point the sonar system behavior is inflexible. Considering the fast changing transmission characteristics of the underwater channel, this is not optimal.

Here the idea of cognitive sonar applies. The concept goes back to early pioneers in cognitive processing, e.g, Simon Haykin who proposed in 2005, based on [4], [5], the idea of cognitive radar [6], [7]. To get an abstract idea of a cognitive system, it can be illustrated with the help of a quotation from the *Oxford English Dictionary,* regarding cognition: It describes “knowing, perceiving, or conceiving as an act”. In the context of a technical system, the interpretation of these three points may lead to:

- 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 2011 some research activities in the field of cognitive sonar were started. Xiaohua investigated the cognitive aspect in combination with receive beamforming in [3] and proposed a more detailed cognitive-sonar concept in [8]. In further research the cognitive aspect is investigated in multiple-input multiple-output (MIMO) sonar systems. Here special orthogonal waveforms are used for target detection. In [9] the authors optimized the transmit beamformer for the specific waveforms. In 2009 Li et al. optimized in [10] environmental sensor parameters of a space-time adaptive processing (STAP) MIMO sonar.

However, compared to the cognitive radar, cognitive sonar drew little attention in the research community. This is incomprehensible when considering that in wildlife a well known cognitive sonar-system has proven its functionality for centuries: the localization system of a bat [6].

In [4] Haykin describes 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 amplitude, frequency, and pulse-repetition rate. They sense the outgoing pulse and compare it with the echoes, reflected by

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the surrounding and potential targets (e.g., insects). Thereby they produce a detailed image of their environment. Bats collect this information to adjust their position as well as the transmission pulse, in order to achieve optimal results of the actual performed task. While bats are searching for a target, they constantly scan the environment with a certain pulse form and a relatively low pulse-repetition rate. As soon as they sense a target, they change the transmission pulse and increase the pulse-repetition rate.

In this paper a cognitive active-sonar system is proposed that works in real-time and combines several techniques of the localization system of the bat with traditional sonar signal processing. We show, in detail, the realization of a matched filter (implemented as a cross-correlation of the transmitted and the received signal), capable to process arbitrary waveforms that match best specific target velocities in a certain environment. To achieve this, a Doppler processing of the generated pulse via a $sin(x)/x$-interpolation is realized.

The desired system behavior can be achieved by the fusion of the tracking-layer data and the sensor-layer data while cognitive adjustments are realized by utilizing target and environment-optimized waveforms and transmit beamforming. The system is tested in Monte-Carlo simulations against traditional sonar signal processing techniques. It can be shown that the system behavior can achieve a higher probability of detection and thus leads to more robust tracks.

The outline is as follows: Section II shows an overview of the signal processing for the cognitive-sonar system, and the particular elements of the setup are described. The subsequent subsections give an overview of transmission signals in the context of cognitive sonar and explain the process of matched filtering by implementing a fast uniformly-partitioned overlap-save convolution in detail. This includes the Doppler processing that is done with a real-time $sin(x)/x$-interpolation of the transmit signal. Simulation results are given in Section III. The last section provides a conclusion and outlook.

II. The cognitive active sonar system

A. Main principle

The main principle of the proposed cognitive-sonar system is its ability to tailor its signal processing to target and environmental parameters. Since it makes use of extra information, it is obvious that an optimally tailored signal processing leads to equal or better results, e.g., in terms of track probability of detection or track false-alarm rate [11], compared to a non-cognitive signal processing. At this point the cognitive approach can be divided into two main parts:

1) The optimal measuring of the target and environmental properties.
2) The optimal utilization of the measured parameters within the signal processing units.

Within the word "optimal" lies the challenging part of the cognitive approach. It implies some sort of objective that the system tries to reach. And it leads to earlier and robuster detection of the target.

In the proposed system the measuring of the target properties is realized by adapting the sensor-layer signal processing

Figure 1. Receiver hardware for the proposed sonar signal processing. The receiver consists of 48 channels. The transmitter (not depicted) consists of 32 channels.

using the data obtained by an internal tracking system. When insecure tracks occur in the tracking layer, the system tries to confirm or terminate them by optimizing subsequent pings in the sensor layer. Further, the system is able to utilize external or environmental information, e.g., position of stationary clutter or water depth, that is given by the user or a device.

The utilization of this information is done by the system with the following two cognitive adjustments:

1) Change the transmit signal to improve the signal-to-noise ratio (SNR) and the signal-to-reverberation ratio (SRR) after Doppler processing and thus the robustness of the probability of detection.
2) Change the direction of the transmit pulse to improve the spatial awareness of the system.

B. Technical boundary conditions

The proposed cognitive-sonar system should be able to work under real conditions in real-time. Therefor, the system design must meet certain criteria that act as boundary conditions. The basis for an active sonar system is the receiver (hydrophone) and the transmitter (projector) hardware. In this contribution the system is built up as a mono-static sonar. In Fig. 1 the receiver hardware is shown. It is designed as an horizontal line array that consists of 48 channels (staves). The transmitter utilizes 32 staves and is able to access each stave separately. This enables the possibility to transmit arbitrary signals and allows transmit beamforming. The transmit frequency lies between 50-80 kHz and the system works at a sample rate of 192 kHz. The hardware is connected via standard multi-channel audio cards to a standard personal computer (PC).

Its specifications and other development informations are:

- Intel XEON quad core CPU, 2.8 GHz,
- Memory: 24 GB, 1333 MHz,
- Windows 7 Professional Edition,
- Microsoft Visual Studio 2012,
- Intel Performance Primitives library.

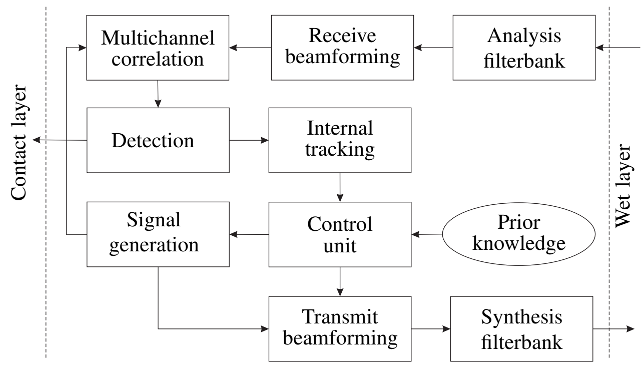

Figure 2. Schematic of the signal processing for a cognitive-sonar system.

C. Signal-processing overview

In Fig. 2 the signal-processing structure of the cognitive-sonar system is depicted. To enable sufficient real-time performance the signal processing is, on the one hand, carried out in the frequency domain and, on the other hand, a band-limited processing technique is used. Since band-limited signals are deployed it is possible to apply the necessary computation only in relevant frequency segments. This technique is further called “frequency-selective estimation”.

In the analysis-filterbank module the received signal is divided into blocks (frames)[1] and transformed via an overlap-add method into the frequency domain. Next a fixed filter-and-sum beamformer that utilizes a Hann window [12] is used to produce a direction matrix.

The multichannel-correlation module works as a matched filter. It is able to correlate the incoming, beamformed signal matrix with the original version and with Doppler-spread versions of the transmit signal. A detailed explanation of this block is found in Section II-E.

After correlation, the detector module generates contacts for further processing. The detector consists of two components: a constant-false-alarm-rate (CFAR) algorithm with range-dependent threshold for normalization and detection as well as an associated connected-component-analysis (CCA) [13]. There are three implemented CFAR-methods available that can be chosen by the user: *cell-averaging-, cell-averaging-greatest-of-,* and *cell-averaging-least-of-*CFAR [14]. After processing the CFAR algorithm the CCA is used to estimate the size and the centroid position of the contacts. The generated contact data is transmitted to an external tracking system[2] and to an internal tracking module. During the further course of this paper, whenever refered to the tracker, the internal tracking module is meant.

A Multi-Hypothesis Tracker (MHT) is utilized based on [15] that is appropriate in case of false alarms or missing detections [16]. When the targets are well separated, this single-target tracker also works in multi-target scenarios [17]. As stated in Section I the tracked data is the basis for the cognitive system behavior. It is processed in the main control unit. At this point all relevant information is gathered to control the signal generation and the transmit beamforming for subsequent pings. A more detailed description of this module is found in the following Subsection II-D.

[1]Typical frame sizes: 64 to 512 samples.

[2]Indicated as contact layer in Fig. 2.

D. Control Unit

The main control unit alternates between two operational modes: the “scan mode” and the “adaptive mode”. In scan mode the system tries to scan its environment in a broad manner and utilizes Doppler-invariant signals, e.g., frequency-modulated (FM) signals (see Section II-E1). If potential targets are identified by the tracker, the main control unit can change the operational mode to adaptive mode where target-specific properties are considered for applying optimized transmission waveforms. This is the case when insecure tracks occur. To quantify the quality of a track the tracker uses a technique that is called “Sequential Track Extraction” [18]. In this method the tracker outputs a track score. If the track score is low, there are two main possibilities:

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

In both cases, an optimized transmit waveform can help to improve the tracking result, since it leads either to raise the track score or to discard the track. In addition to that the transmit beamformer is able to block the transmission of the sound pulse in the direction of known clutter. This behavior can be conducted from outside, e.g., either the user who has a-priori information, or the system is able to identify stationary interferers during run-time.

When target-specific wave forms and transmit-beamforming patterns are used, the system is getting blind for the major environment. Only particular targets are illuminated. Therefore the scan mode and the adaptive mode should be switched in a regular heuristic. While in the current implementation the scan mode and the adaptive mode are alternating, a further improvement would be to use individual transmit patterns that are optimized for the individual targets' distances. Thus, the inter-ping interval could be reduced, the pulse repetition rate increased, and thus the information flow per time.

E. Doppler processing

An active sonar system needs to face two major kinds of impairments that affect the detection of a target. The first one is the environmental noise covering the target inside an unwanted signal. The second is the reverberation masking the target in unwanted reflections of the transmitted signal [1].

Using a matched filter implemented as a cross-correlation of the transmitted with the received signal addresses both of the impairments mentioned above. The cross-correlation is able to improve the signal-to-noise ratio (SNR) and, considering the Doppler effect, is capable of filtering targets of a certain velocity out of the reverberation [19]. These abilities are highly depending on the signal design of the transmitted signal, which, again, depends on the desired properties of a certain sonar system.

The following subsection shows known sonar signals and discusses signal properties a sonar designer should take into account when optimizing the system. After that, an efficient real-time implementation of a $sin(x)/x$-interpolation-based Doppler processing and a frame-based frequency domain implementation of a correlation module is shown in detail.

1) Signals: When designing a transmit signal for sonar systems, the corresponding cross-correlation properties are important. The most crucial features are the pulse-compression ability of a signal resulting in a better range resolution and the capability of gaining a higher SNR. Another important cross-correlation feature is the Doppler sensitivity. When the transmit signal is reflected on moving objects, the signal undergoes a Doppler spread and shift. With a Doppler-sensitive (Doppler variance) signal it is possible to distinguish between targets of different radial velocities.

To assess a certain sonar signal design, the ambiguity function is an important tool to analyze the features of a particular transmit signal. It visualizes the matched-filter (cross-correlation) output as a function of delay and Doppler frequency shift f_D [19]. In the case of narrowband signals, the ambiguity function of a time-depending signal $s(t)$ is given by [20]:

$$X_s(\tau, f_D) = \int_{-\infty}^{\infty} s^*(t) s(t+\tau) \exp(j2\pi f_D t)\ dt. \quad (1)$$

For wideband signals, the Doppler-frequency shift can not be assumed to be constant anymore. It leads to a wave compression or stretching depending on whether the radial velocity is negative or positive. A scaling factor is defined which corresponds to the compression ratio [19]:

$$\eta = \frac{1 + v/c}{1 - v/c} \approx 1 + \frac{2v}{c}. \quad (2)$$

Here v denotes the radial velocity of a target towards the receiver and c the speed of sound in water.

The factor η is used for calculating the wave compression by interpolation of the transmit signal (see II-E2) and the ambiguity function for a wideband signal can be defined as [21]:

$$X_s(\tau, \eta) = \int_{-\infty}^{\infty} s^*(t) s(\eta(t+\tau))\ dt. \quad (3)$$

The proposed system is designed to switch to the desired waveform while operating, depending on the operational mode. While in scan mode, Doppler invariant signals can be a good starting point, depending on the actual environment. As stated, the FM signal, or linear FM (LFM) signal, is a highly common Doppler-invariant transmit signal. In time domain the LFM signal is given by:

$$s(t) = w(t) \cdot \Re\left\{ e^{j2\pi(f_0 t + (BWt^2)/(2T))} \right\}, \quad (4)$$

where $w(t)$ is the amplitude window of the pulse, BW denotes the bandwidth of the signal, f_0 is the starting frequency, and T the pulse duration.

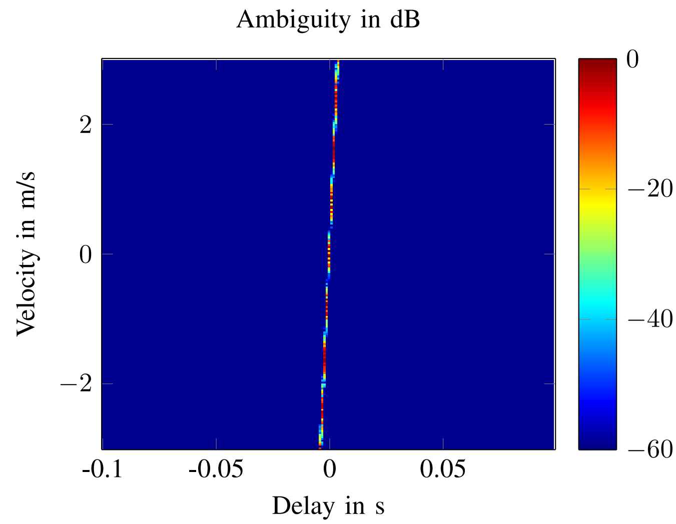

Figure 3. Ambiguity function for a linear FM pulse of 100 ms length, a center frequency of 70 kHz and a bandwidth of 7500 kHz.

The ambiguity diagram of a Hann-windowed linear FM signal with a center frequency of 70 kHz, a bandwidth of 7.5 kHz and a signal length of 100 ms is shown in Fig. 3. The ambiguity function displays a thin line over radial velocities between -3 and 3 m per second. The line is slightly diagonal, due to the time shift needed to match the frequency shift of the Doppler effect; this will lead to a certain range-estimation error, depending on the velocity of the target.

Fig. 4 shows an ambiguity diagram for a pseudo-random-noise (PRN) signal. The signal is generated as a white Gaussian noise sequence of a length of 100 ms and bandpass filtered with a center frequency of 70 kHz and a bandwidth of 7500 kHz. Fig. 4 shows a narrow peak in the center and a uniform sidelobe level in range and Doppler axis. This signal serves as example of a signal with highly Doppler-variant properties and thus seems to be an optimal choice for a waveform used in scan mode. However, in highly cluttered environments, the relatively high sidelobe level can lead to poor detection probabilities [21]. Depending on the operational environment the sonar designer can choose signals for various conditions with various advantages and disadvantages [20], [19], [21].

There are situations, where low Doppler-sensitivity (Doppler invariance) is preferred. Especially in low-reverberative environments and when targets moving in a larger potential radial-velocity interval, it could be desired to cover all potential targets despite the radial velocity. For the case of heavily cluttered environment or if the target of interest moves within a particular radial-speed interval like in most diver detection scenarios, a different behavior is useful. Extracting a target from other objects, considering the Doppler shift, respectively the radial velocity, can significantly increase the detection rate. A good choice for this scenario is the sinusoidal frequency modulation (SFM) signal:

$$s(t) = w(t) \cdot \Re\left\{ e^{j2\pi f_c + j\beta \sin(2\pi f_m t)} \right\}. \quad (5)$$

Here f_m is the modulation frequency and β is the modula-

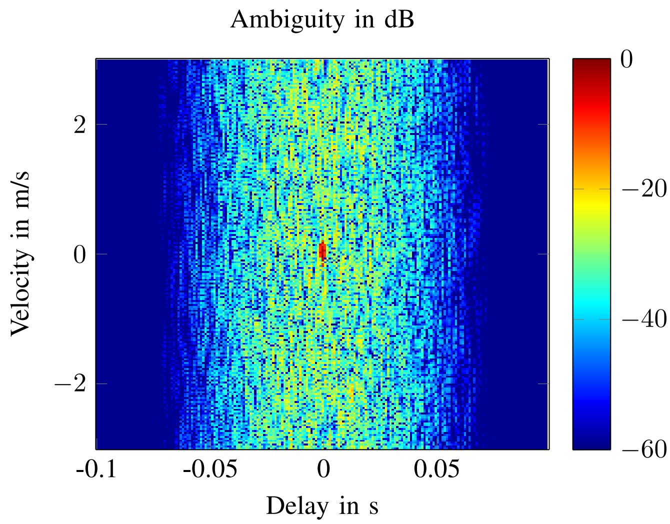

Figure 4. Ambiguity function for a PRN signal pulse of 100 ms legth, bandpass filtered with a center frequency of 70 kHz and a bandwidth of 7500 kHz.

tion index that determines the bandwidth of the signal. f_m is the frequency of a second sinusoid which defines the frequency spacing of spectral peaks. The SFM signal is a modification of a continuous wave (CW) signal design and provides Doppler sensitivity without the downside of providing high sidelobe levels like the PRN signal. On the other hand it serves a certain range ambiguity but not as much as the CW signal [19]. The superior behavior, in terms of probability of detection, of the SFM signal compared to a FM signal in reverberation limited environments is shown in Section III, Fig. 7.

2) Interpolation: When Doppler-sensitive signals are used, it is essential to conduct the correlation process with the corresponding Doppler-spread replica of the reference signal. To enhance the flexibility of the system, a real-time interpolation algorithm is used to create a replica that matches to the radial velocity of a certain target at the current ping period.

The basic idea of the interpolation is known from sample-rate conversion techniques. Here an ideal low-pass filter is used to compute a continuous time signal z from the discrete reference signal x:

$$z(t) = \sum_{\kappa=-\infty}^{\infty} x(\kappa T_A) \cdot h(t - \kappa T_A), \tag{6}$$

with h being the continuous si-function:

$$h(t) = \frac{\sin\left(\frac{\pi t}{T_A}\right)}{\frac{\pi t}{T_A}}, \tag{7}$$

where t denotes the continuous time index and T_A the sample distance of x. In addition it defines the width of the low pass filter, respectively the location of the zeros of the si-function. Afterwards the continuous signal gets resampled to obtain the desired sample rate.

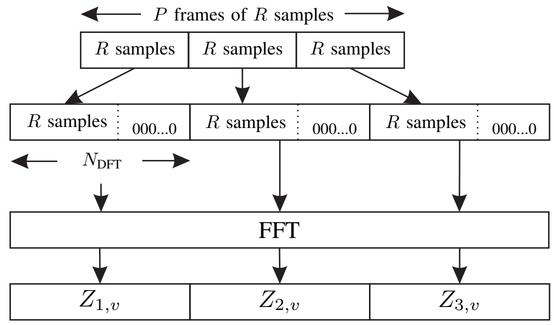

Figure 5. Partitioning of the transmit signal z_v in P_v frames of R samples and zero-padding to the length N_{DFT}.

This method is characterized by a large computational complexity and delay. To solve this issue, a common method is the truncated si-interpolation which is an approximated version of (6) and leading to the signal:

$$\widetilde{z}(n) = \sum_{\kappa=-N}^{N} x(n-\kappa) \cdot h(n\widetilde{T}_A - (n-\kappa)T_A), \tag{8}$$

where the parameter $\widetilde{T}_A$ indicates the sampling time of the output signal and n the discrete time index. The filter response h can be stored in an oversampled manner to save computational load. The delay of this method requires about N = 32 to 64 samples for reasonable choices.

When applying this technique for Doppler interpolation the Doppler spread factor Δs is an essential parameter:

$$\Delta s = 1 \pm \frac{v_t}{c}, \tag{9}$$

with v_t being the relative radial velocity of the target towards the receiver and c the propagation velocity of the medium (e.g. 1500 meter per second).

The approximate Doppler si-interpolation for an output signal z_v for the v-th target velocity can be written as:

$$z_v(n) = \sum_{\kappa=0}^{N_h-1} x(I(n, \Delta s_v) - \kappa) \cdot h_{int}(\kappa, n, \Delta s_v), \tag{10}$$

where h_{int} contains the truncated si-function. The filter length is N_h and the index for the integer-delay part of the interpolation is given as:

$$I(n, \Delta s_v) = \lfloor n \cdot (\Delta s_v + 1) \rfloor, \tag{11}$$

and the fractional-delay part as:

$$h_{int}(k, n, \Delta s_v) = \widetilde{h}_{int}(\delta(n, \Delta s_v) + k \cdot L). \tag{12}$$

$\widetilde{h}_{int}$ contains the oversampled si-function with length of $\widetilde{N}_h = N_h \cdot L$:

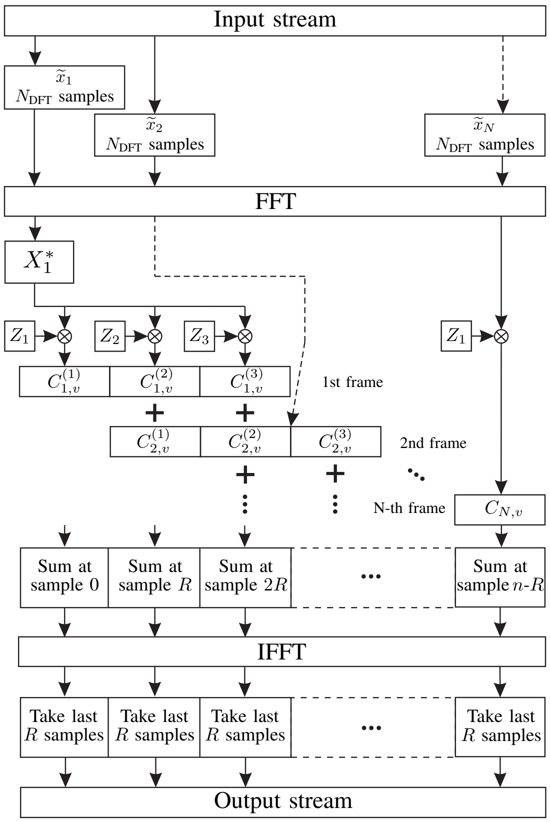

Figure 6. Schematic depiction of the Uniformly-partitioned overlap-save correlation algorithm at runtime with $P_v = 3$.

$$\widetilde{h}_{int}(i) = \frac{\sin\left(\frac{i}{L} \cdot \pi - \frac{\widetilde{N}_h}{2}\right)}{\left(\frac{i}{L} \cdot \pi - \frac{\widetilde{N}_h}{2}\right)} \cdot w\left(i - \frac{\widetilde{N}_h}{2}\right), \tag{13}$$

where L defines the resolution and thus the zeros of h_{int}. The function δ gives the index of the the fractional delay part of the filter response h_{int}:

$$\delta(i, v) = \lfloor \Delta s_v \cdot i \cdot L \rceil \bmod L. \tag{14}$$

3) Uniformly-partitioned overlap-save correlation: The uniformly-partitioned overlap-save correlation dates back to an algorithm for convolution on a digital-signal-processing (DSP) chip for audio applications, proposed 1966 in [22] and further investigated on a DSP board in [23].

Within this module the short signal pulse z_v that was generated in the Doppler interpolation module is correlated with a constant input data stream x. In this overlap-save correlation implementation, the first step is to partition z_v into zero-padded blocks of size N_{DFT}:

$$\widetilde{z}_{p,v}(m) = \begin{cases} z_v(m + p \cdot R), & \text{if } 0 \leq m \leq R - 1 \\ 0, & \text{else} \end{cases}, \tag{15}$$

where the integer m is the sample index in the range of $0 \leq m \leq N_{DFT} - 1$ and p the frame index of the interpolated

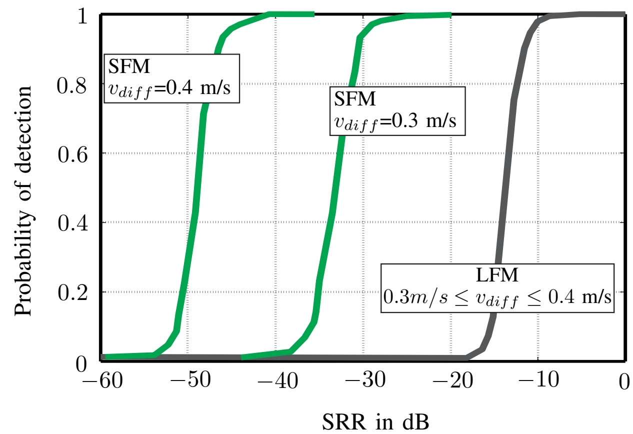

Figure 7. Detection probabilities for a LFM signal compared to a SFM over SRR.

transmit signal. p lies in the range of $0 \leq p \leq P_v - 1$ with $P_v = \left\lceil \frac{N_v}{R} \right\rceil$ and N_v being the number of samples from the transmit signal of the v-th target velocity. $\widetilde{z}_{p,v}$ is transformed with the Discrete Fourier Transformation (DFT) into the frequency domain which results in $Z_{p,v}$. To minimize computational complexity the Fast Fourier Transformation (FFT) algorithm is used (see Fig. 5).

The continuous input data stream from the beamformer output x is divided into frames of length N_{DFT}. The frames overlap and each overlapping block begins $N_{\text{DFT}} - R$ samples after the previous one:

$$\widetilde{x}_k(m) = \begin{cases} x(m + k \cdot R), & \text{if } k \geq 0 \\ 0, & \text{else} \end{cases}. \tag{16}$$

Here the integer value k denotes the frame index. A negative k value is explicitly not excluded, because in the following part of the algorithm negative values for k are possible. The frames are transformed into the frequency domain via the FFT algorithm resulting in X_k.

To reverse the order of samples in the time domain, the conjugate complex of X_k is computed before it is multiplied with each P_v frame of the stored transmit signal spectrum $Z_{p,v}$. The result is accumulated over the P_v frames which leads to:

$$C_{k,v}(\mu) = \sum_{i=0}^{P_v} X_{k-i}^*(\mu) \cdot Z_{i,v}(\mu). \tag{17}$$

$C_{k,v}$ is transformed via the Inverse Fast Fourier Transformation (IFFT) algorithm into the time domain which results in $c_{k,v}$. To obtain the desired frame of length R, only the first R samples are considered to form the output stream:

$$y_{v,k}(l) = c_{k,v}(l + N_{DFT} - R), \tag{18}$$

where the sample index l lies in the range of $0 \leq l \leq R - 1$. Fig. 6 shows the scheme of the correlation algorithm with $P_v = 3$.

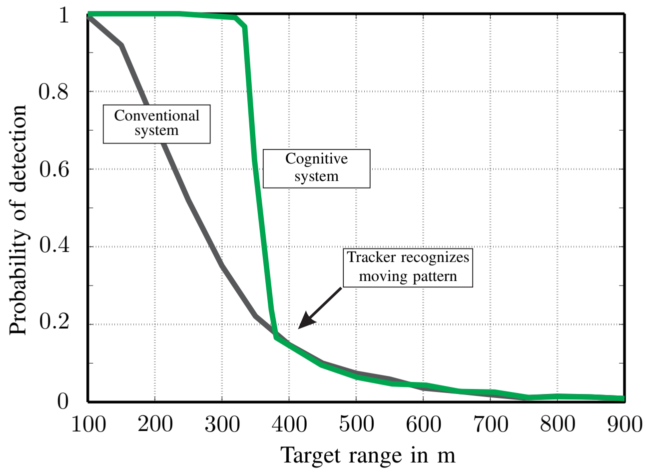

Figure 8. Probability of detection over range in a reverbarative, single target scenario for a conventional sonar system that utilizes a FM transmit signal (left) and the cognitive sonar system (right).

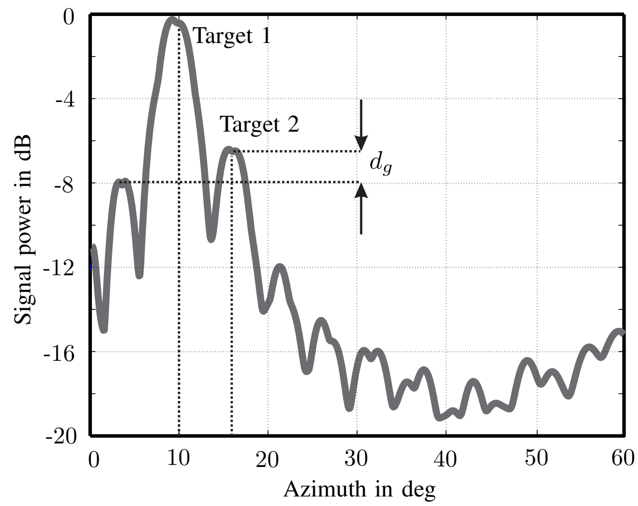

Figure 9. Averaged power output of the beamformer module in the presence of two targets. Target 1 in 10 degree direction, target 2 in 15 degree direction. Target 2 has a 10 dB lower target strength than target 1 what leads o a low detection performance.

The computational complexity of this algorithm can be improved by optimizing the computations in the frequency domain via two steps:

1) Due to the symmetry of the time- and frequency domain and the usage of real signals, computations only need to be done in the first half of the complex spectrum[3].
2) Since band-limited signals are used, the frequency selective estimation, mentioned in Section II-C can be applied. With this technique the computation is only carried out in the relevant frequency bins.

III. Simulation results

A. Doppler processing

Sonar systems for diver detection are usually located in coastal areas or harbors. As stated in Section II-E, these scenarios usually offer a reverberation limited environment. There are many different kinds of reverberation and the scattering strength depends on many factors [24], [19], [25]. To show the potential of the utilization of a Doppler processing in a reverberative environment the detection probabilities for different transmit signals are given in Fig. 7. There are two signals under test: the first one is a LFM pulse with T=100, a center frequency of 70 kHz and the bandwidth BW=7500 Hz. This signal is Doppler invariant, hence Doppler processing will not lead to a better separation of the moving target from the scatters. The second signal is a Doppler variant SFM with the same values for T and BW(compare Section II-E1). The signal-to-reverberation ratios (SRR) in these simulations are controlled by changing the reverberation values. The signal energy is normalized to unity and the target radial velocity towards the receiver is given with v_{diff}=0.4, respectively v_{diff}=0.3 meters per second.

It can be seen that, regardless of the velocity, with SRR values around -10 dB the system is able to reliably detect the target with a LFM pulse. In this case there is no need for utilizing different transmit signals. For lower SRR values around -20 dB the sonar system is not able to detect the target with an LFM signal anymore. Depending on the radial velocity v_{diff} the detection performance can be significantly increased using a Doppler variant pulse (in this case a SFM pulse) with a matching Doppler processing. The higher the velocity difference, the higher are the performance gains can be achieved with a Doppler variant signal with respect to the SRR. This performance gain at high reverberation values leads to the drawback that only certain velocity ranges are covered with a specific Doppler variant signal.

The cognitive-sonar system utilizes movement information obtained by the tracker to determine the transmitted signal as explained in detail in Section II-C. To investigate the behavior of the system Monte Carlo simulations are carried out. These simulations considers the bottom reverberation as the dominant scatter. The reverberation is assumed to be stationary and uniformly distributed over range. The back-scattering strength is about -35 dB [24], [25]. It is a one-target scenario where the target moves between 900 and 100 meter with a constant velocity of 0.3 meter per second towards the receiver and a target strength of -10 dB. In Fig. 8 the results of the Monte Carlo simulations are visualized. It shows the probability of detection resulting from the detection unit over the target distance. The left (black) graph shows an approach where only a LFM pulse with T=100, a center frequency of 70 kHz and the bandwidth BW=7500 Hz is used.

The right (green) graph depicts the simulation results of the cognitive-sonar system. Initially, in scan mode, the system utilizes the same LFM transmit signal as the traditional approach resulting in the same probability of detection results. At the range of about 400 meter (marked with the arrow) the tracker is able detect a movement pattern at a certain speed range. This track is weak in terms of the track score. Nevertheless, the system uses the obtained information to adapt its transmit signal. This results in a significant increase of the detection probability and thus results in a stable track quality.

[3]Merging the processed bins with its symmetric complex conjugate before applying the IFFT is assumed.

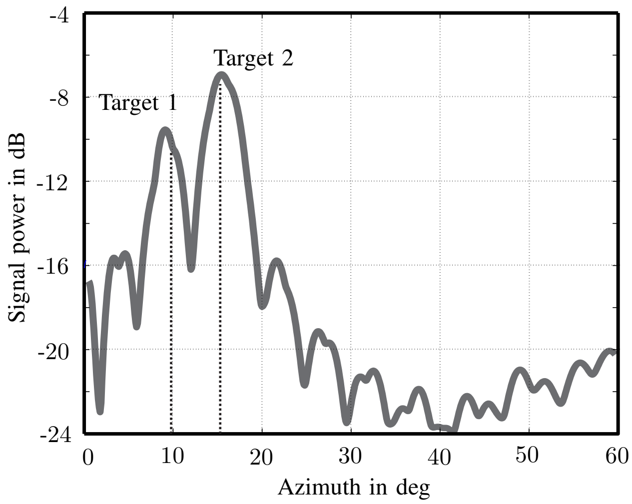

Figure 10. Averaged power output of the beamformer module in the presence of two targets. Target 1 in 10 degree direction, target 2 in 15 degree direction. Target 2 has a 10 dB lower target strength than target 1. In this scenario a transmit beamformer is used to block the sound propagation in the direction of target 1.

B. Transmit beamforming

To illustrate the advantage of transmit beamforming Fig. 9 shows the averaged power output of the receive beamformer module. In the observed scenario are two targets present: the first at a azimuth of 10 degree[4] (target 1) the second at a azimuth of 15 degree (target 2). The target strength of target 2 is about -10 dB lower compared to target 1. Because of the imperfection of the receive beamformer, target 2 is "covered" within the sidelobe of target 1. The difference d_g between sidelobe and target is about 1.5 dB. This leads to low a low detectability because it is difficult for the detector to distinguish between a sidelobe and a real target. Using a Transmit beamformer can reduce this problem by reducing the transmitted energy in the direction of the interferer. The result in Fig. 10 shows the expected behavior. Through reduction of the acoustical illumination in target 1 direction the interfering sidelobes are reduced and the target 2 is clearly visible.

IV. Conclusion and Outlook

In this contribution a cognitive-sonar system was presented and a key part of the system, the real-time Doppler processing, was shown in detail. The proposed system utilizes the information obtained by a tracking algorithm within the sensor layer. This information is used to adapt its signal processing and hence to improve the detection rate. The cognitive adjustments are carried out by changing the transmit signal and the direction of the transmitted energy. It could be shown in simulations that this technique can lead to a higher and robust detection probability compared to traditional sonar systems.

The research on this topic is still evolving. Hence further investigations are necessary to improve this concept in a real-live environment. Especially the transmit patterns and the track-score threshold should be part of future investigations. Furthermore, the additionally gained information of specific target velocities within this concept, makes room for an improved signal design. This signal design should focus on a "peak like" structure in the velocity plane of the ambiguity function and a low sidelobe level.

[4]While 0 degree means broadside.

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