Cognitive Radar Performance Analysis with different Types of Targets

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Abstract— **In this paper, experimental results with the CODIR cognitive radar testbed are presented. Different optimization objectives for the tracking performance and/or the radar resource usage have been considered to test the optimization capability under various conditions. For that, a new generalized cost function has been defined that can be parameterized to the different objectives. The radar resource usage and the tracking performance has been analyzed using DGPS ground truth data. The system is able to adapt its radar parameter in real-time to meet one or a combinations of objectives. In the case of optimizing multiple conflicting objectives the relative prioritization can be adjusted and the system adapts its radar parameters accordingly.**

Keywords— cognitive radar, experiments, waveform optimization, multi-objective optimization

I. Introduction

Novel radio frequency (RF) technologies and concepts such as software defined radio (SDR), arbitrary waveform generation (AWG) and digital signal processing (DSP) trigger new possibilities of real-time optimizing and tuning a radar system to the current operational goal and environment. To exploit these degrees of freedom several cognitive-inspired concepts and algorithms have been proposed and first algorithms have been implemented in experimental testbeds.

Cognitive-inspired techniques in radar mimic elements of human cognition such as the perception-action cycle [1], learning, anticipation [2] and the used of external knowledge [3]. The human perception-action cycle can be adapted to radar by analyzing the current radar data and act on short timescale by adapting transmit, receive and processing parameters for an optimal use of radar resources and to fulfil performance goals in the given environment. In the last few years, substantial conceptual, theoretical, and modelling work has been done. First experimental work to implement the perception-action cycle for different radar applications such as tracking [4], [5], imaging [6] and jammer mitigation [7] are available.

In this paper, we present a radar testbed with an implemented perception-action cycle and demonstrate the performance and the optimal use of resources in an outdoor environment and with different targets. In Sect. II, we present the radar testbed and in Sect. III, the experimental setup and the optimization objectives are described. Results are presented in Sect. IV and the present work is concluded in Sect. V.

II. The CODIR Testbed

The CODIR ("COgnitive Detection, Identification and Ranging") testbed consists of an X-band radar sensor and a controller segment which tracks the target and selects the optimal radar parameters based on the past sensor perception (measured position, SNR, measurement accuracy). By feeding the sensor perception back to the optimizer a perception-action cycle is defined.

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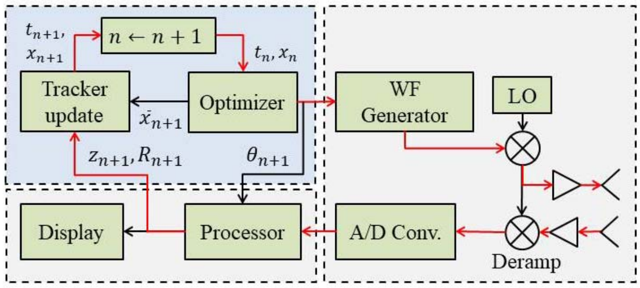

Fig. 1. CODIR block diagram. The controller is highlighted in blue. Red arrows mark the implemented perception action cycle.

A. The CODIR Sensor

The sensor transmits a linear frequency modulated (LFM) waveform with an adaptive instantaneous bandwidth (BW), an adaptive chirp length and an adaptive pulse repetition frequency (PRF). The received signal is mixed with the transmit signal and the corresponding beat frequency signal is A/D converted with a sampling rate of $f_s = 50\,\mathrm{MHz}$. The digital signal processing consists of a range-Doppler (RD) processing step with an adaptive length of the coherent processing interval (CPI) and with moving target indication (MTI)-filtering to suppress ground clutter returns. A detector which extracts the amplitude maximum in the RD map is implemented. The corresponding measurement vector is

$$\boldsymbol{z} = (R, v, \mathrm{SNR}), \tag{1}$$

where R is the range, $v = \dot{R}$ is the range rate and SNR is the signal-to-noise ratio, defined as the peak-to-sidelobe amplitude ratio in the RD-map, calculated in dB.

B. The CODIR Controller

1) Tracker

The CODIR controller consists of a single target tracker and an optimizer which selects the optimal radar parameters at each track update. The tracker employs a standard Kalman filter and a constant acceleration model using the following state vector

$$\boldsymbol{x} = (R, v, \mathrm{SNR}_{\mathrm{red}}), \tag{2}$$

where $\mathrm{SNR}_{\mathrm{red}}$ is the reduced SNR defined as

$$\mathrm{SNR}_{\mathrm{red}} = \mathrm{SNR} - 10\log(N) + I(\theta) - 10\log(\sqrt{D}) - 10\log\left(\left|\sin\left(\frac{2\pi v f_c T}{c}\right)\right|\right) \tag{3}$$

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Here, $T = 1/\mathrm{PRF}$ is the pulse repetition interval, N is the number of samples per chirp, f_c is the carrier frequency, D is the number of chirps in the CPI and $\mathrm{I}(\theta) \sim 10 \log(\sqrt{\mathrm{N}})$ is the amplitude noise level for this waveform. With the definition (3) we split radar parameter dependent contributions to the SNR from other contributions such as range. Known dependences of the SNR on the implemented MTI filter and on the integration time, determined by chirp size and CPI length are used. Besides the standard expressions for the transition matrix, the measurement matrix and the process noise covariance we use the following expression for the measurement covariance matrix

$$R = \mathrm{diag}(C_0\sigma_R^2, C_0\sigma_v^2, \sigma_{SNR}^2), \quad (4)$$

where $\sigma_R = c/2B * N/N_{FFT}$ and $\sigma_v = c/(2f_cTD)$ are the range and velocity cell sizes in the RD plane. Here, N_{FFT} is the length of the range FFT and $\sigma_{SNR}^2 = 5$ is experimentally defined. Finally, the factor

$$\mathrm{C}_0 = \max(1{,}1000 * (1 - H(\mathrm{SNR} - \mathrm{SNR}_0)) \quad (5)$$

models the additional uncertainty at small SNR values in a phenomenological way. Here, H is the Heavyside step function and $\mathrm{SNR}_0 = 2$ is an experimentally defined detection threshold.

2) Optimizer

The optimizer implementation is based on [8], [9] and its adaptation to the CODIR sensor [10]. The optimization is done at each track update and consists of the following steps:

TABLE I. OPTIMIZER IMPLEMENTATION

Input: t_n, x_n
For each allowed parameter set θ calculate: • A priori track update $\bar{x}(\theta)$ • Predicted conditional Bayes information matrix (PC-BIM, see [8]) $B^{\uparrow}(\theta)$ • Predicted track uncertainties $\alpha_R = [B^{\uparrow}(\theta)^{-1}]_{11}$ and $\alpha_v = [B^{\uparrow}(\theta)^{-1}]_{22}$ • Cost function value $\mathrm{C}(\theta, \bar{\mathrm{x}}(\theta), \alpha_R(\theta), \alpha_v(\theta))$
Determine optimize parameter set $\theta_{n+1} = \underset{\theta}{\mathrm{argmin}}\, \mathrm{C}(\theta, \bar{\mathrm{x}}(\theta), \alpha_R(\theta), \alpha_v(\theta))$
Output: $\theta_{n+1}, \bar{x}_{n+1} = \bar{x}(\theta_{n+1}), t_{n+1} = t(\theta_{n+1})$

The optimized radar parameter set θ_{n+1} is passed on to the WF generator and the processor to update the sensor. The a priori target state $\bar{x}_{n+1} = \bar{x}(\theta_{n+1})$ is needed by the tracker to update the target state as soon as a new measurement z_{n+1} is available.

C. Generalized Cost Function

The cost function measures the cost to perform the measurement and the cost to assure the track accuracy. It is a scalar function that depends on the radar parameter set θ and the track uncertainty measured by the PC-BIM. We use the following generalized cost function modelled as a weighted sum of single objective costs with weighting parameters w_i [11]:

$$\mathrm{C}(\theta) = \sum w_i C_i(\theta) = \sum w_i \frac{X_i(\theta) - X_{i,0}}{X_{i,1} - X_{i,0}}. \quad (6)$$

Here, $X_i = (B, T, D, N, \alpha_R, \alpha_v)$ are the radar parameters and track uncertainties, $X_{i,0} = (X_{B,0}, X_{T,0}, X_{D,0}, X_{N,0}, X_{\alpha R,0}, X_{\alpha v,0})$ are the corresponding single objective goal values and $X_{i,1} = (X_{B,1}, X_{T,1}, X_{D,1}, X_{N,1}, X_{\alpha R,1}, X_{\alpha v,1})$ are the corresponding least favorable values. The normalization of the single objective cost to the unit interval [0, 1] enables a comparison between different single objective costs. By selecting the normalized weights $w_i = (w_B, w_T, w_D, w_N, w_{\alpha R}, w_{\alpha v})$ we are enable to modify the relative importance of the single objectives and therefore to define top-level objective.

In the following, we define the following three conflicting top-level objectives (denoted as "T", "B" and "A", respectively):

- "T": Time effort minimization ($D * T \rightarrow \min$): $w_D^T = 0.5, w_T^T = 0.5$, all other $w_i^T = 0$
- "B": Bandwidth minimization ($B \rightarrow \min$): $w_B^B = 1$, all other $w_i^B = 0$
- "A": Minimal track uncertainty ($\alpha_R, \alpha_v \rightarrow \min$): $w_{\alpha R}^A = 0.5, w_{\alpha v}^A = 0.5$, all other $w_i^A = 0$

In a multi-objective optimization (MOO) scenario several top-level objectives need to be optimized simultaneously and a relative importance between the different top-level objectives has to be defined. Contrary to [11], where the "A" objective has been implemented as a boundary condition, we implement the "A" objective similarly as the other top-level objectives. We introduce a relative weighting between the top-level objectives by multiply the corresponding single objective weight by a top-level weight $q_j = (q_T, q_B, q_A)$.The final single objective weights are then given as a following linear combination:

$$w_i = \sum_j q_j w_i^j \quad (7)$$

III. EXPERIMENTAL SETUP

A. Targets

We consider an outdoor scenario with a target moving in a circular loop between roughly 30 m and 100 m from the radar. Tests are done with the following four different type of target:

TABLE II. TARGETS

Target	Velocity Spread	Remarks
Motor car	|v|< 8 m/s	Range and velocity spread over several cells
Bicycle with cyclist	|v|< 5 m/s	Some velocity spread due to micro motion
Radio controlled Buggy	|v|< 9 m/s	Size 78 cm x 49 cm, large accelerations, more difficult to track
Lawn tractor	|v|< 1 m/s	Slow, nearly constant velocity, target near zero Doppler

B. Radar Parameters and Waveforms

We use a discrete optimization space by defining a library of LFM waveforms (WF), a list of PRF values and a list of CPI lengths. The controller is able to select the WF, the PRF value and the CPI value independently. The

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considered PRF list is given by [0.5 kHz, 1 kHz and 2 kHz] and the allowed CPI length list is [32, 64 and 128]. The list of WFs is given in TABLE III.

TABLE III. LIST OF LFM WFS FOR OPTIMIZATION

WF Nb.	B (MHz)	T_p (us)	$N = T_p f_s$
1	60	2.88	144
7	120	2.88	144
8	120	5.76	288
13	240	2.88	144
14	240	5.76	288
15	240	11.52	576
20	480	5.76	288
21	480	11.52	576
22	480	23.04	1152
27	960	11.52	576
28	960	23.04	1152
29	960	34.56	1728
30	960	46.08	2304

C. *Target ground truth data*

In order to do a performance analysis of the radar data, independent position data of the targets has been collected with a JAVAD GPS logger attached to each target. The logger data has been post-processed and correlated with reference data from a nearby base station to achieve a DGPS accuracy. Ground truth velocities are obtained by numerical differentiation. The ground truth data is converted to the sensor based coordinate system and interpolated to the time stamps of the track data. Deviations from measurements and tracks are obtained by subtracting the ground truth data from the sensor measurements and tracked data, respectively.

D. *Optimization scenarios*

We consider the following two MOO scenarios which each combining different top-level objectives.

1) *Time effort and track uncertainty minimization*

Here, we minimize the time effort for a measurement ("T" top-level objective) while keeping the track uncertainty small ("A"). Different top-level weights are considered. Top-level objective "B" (bandwidth minimization) is not optimized, i.e. $q_B = 0$. The corresponding single objective weights are given in TABLE IV.

TABLE IV. SINGLE OBJECTIVE WEIGHTS FOR SCENARIO 1)

	q_T	q_A	w_B	w_T	w_D	w_N	$w_{\alpha R}$	$w_{\alpha v}$
TA1	0.1	0.9	0	0.05	0.05	0	0.45	0.45
TA2	0.3	0.7	0	0.15	0.15	0	0.35	0.35
TA3	0.5	0.5	0	0.25	0.25	0	0.25	0.25
TA4	0.7	0.3	0	0.35	0.35	0	0.15	0.15
TA5	0.8	0.2	0	0.4	0.4	0	0.1	0.1
TA6	0.9	0.1	0	0.45	0.45	0	0.05	0.05

2) *Bandwidth and track uncertainty minimization*

Here, we minimize the bandwidth ("B" top-level objective) while keeping the track accuracy small ("A). No time effort optimization is done, i.e. $q_T = 0$. Measurements with the single objectives weights given in TABLE V. have been performed.

TABLE V. SINGLE OBJECTIVE WEIGHTS FOR SCENARIO 2)

	q_B	q_A	w_B	w_T	w_D	w_N	$w_{\alpha R}$	$w_{\alpha v}$
BA1	0.1	0.9	0.1	0	0	0	0.45	0.45
BA2	0.3	0.7	0.3	0	0	0	0.35	0.35
BA3	0.5	0.5	0.5	0	0	0	0.25	0.25
BA4	0.7	0.3	0.7	0	0	0	0.15	0.15
BA5	0.9	0.1	0.8	0	0	0	0.1	0.1

Through all the measurement, we use the following goal values:

$X_{B,0}$ (MHz)	$X_{T,0}$ (ms)	$X_{D,0}$	$X_{N,0}$	$X_{\alpha R,0}$ (m)	$X_{\alpha v,0}$ (m/s)
60	2	32	144	0	0
$X_{B,1}$ (MHz)	$X_{T,1}$ (ms)	$X_{D,1}$	$X_{N,1}$	$X_{\alpha R,1}$ (m)	$X_{\alpha v,1}$ (m/s)
960	0.5	128	2304	0.3	0.3

IV. RESULTS

We have performed measurements with real-time optimization using the four targets given in TABLE II. and with the objective weights given in Sect. III.C.

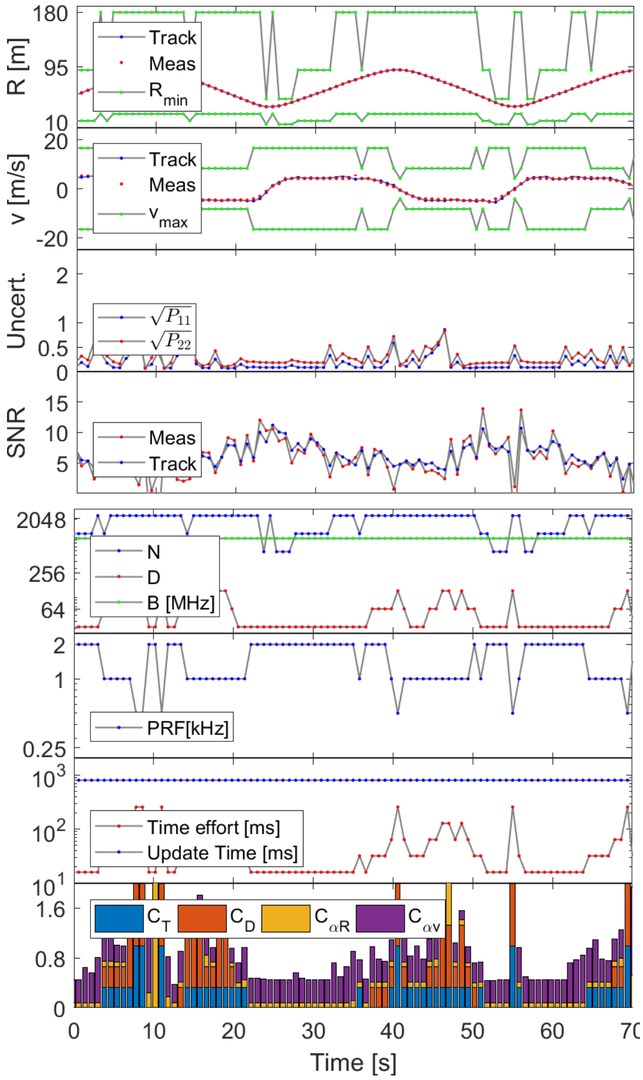

Fig. 2. Optimized radar performance and radar setting choice for bicycle target with the T3 set of weights. Panels from top to bottom: a) Range and velocity evolution (red: measurements, blue: track, green: range limits); b) Track uncertainty defined by the a posteriori covariance matrix **P**; c) SINR (red: measurement from RD map, blue: track); d) Radar parameter evolution ($B, N, T = 1/\text{PRF}$ and D); e) Measurement time effort (red), tracker update time (blue); f) single objective costs. Only the single objective costs with non-zero weights are shown.

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An example of an optimized measurement is given in Fig. 2 where the bicycle target together with the TA3 single objective weight set has been considered. This set minimizes time effort and track uncertainty with equal prioritization. As a consequence, the optimizer selects a radar parameter set with minimal T and D whenever possible but enforces the track accuracy at large ranges and near zero Doppler by increasing T and/or D if necessary. In these cases, the increased single objective costs related to T and D had been balanced against the predicted single objective costs related to track uncertainty. In the following, we analyze in detail how different weight combinations and target types influence the tracking performance.

A. *Minimal time effort versus track accuracy*

In the scenario 1), we optimize the "T" and the "A" top-level objectives at the same time. The relative prioritization shifts from "A" (weight set TA1 with focus in track accuracy) to "T" (weight set TA5 with focus on time effort minimization). The corresponding effect on the tracking performance is exemplarily shown in Fig. 3 where the measured and tracked velocity deviations are shown.

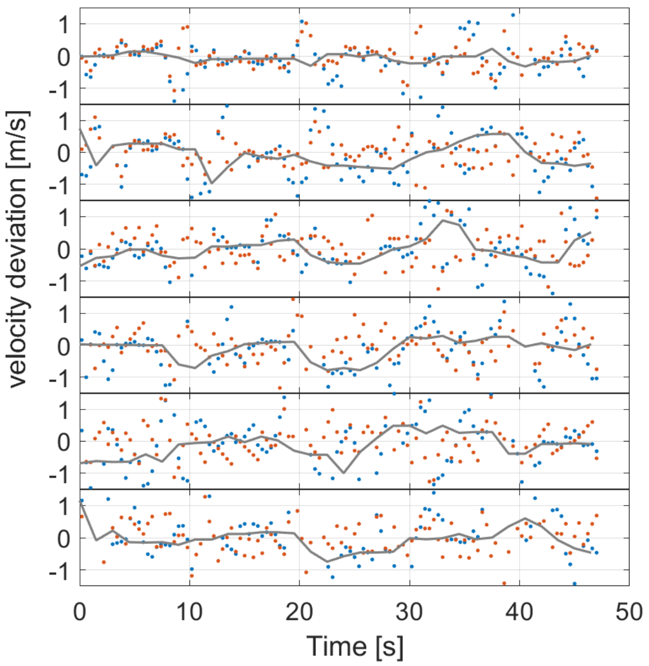

Fig. 3. Deviation of velocity measurements (red) and track (blue) updates with the TA1 (top panel) to TA6 (bottom panel) weight sets and with the buggy target. The track updates are smoothed with a sliding window (grey line) for an indication of the averaged track accuracy over time.

The increase of velocity deviation is clearly visible when the optimization priority shifts from "A" (top panel) to "T" (bottom panel). On the other hand, the range deviation dependency on the different weight sets is much smaller because the bandwidth, which determines the range measurement and tracking accuracy, is not optimized and the controller always selects the largest possible value.

To quantify the tracking performance for a given weight set we define the following metrics:

- Track error is defined as the standard deviation of the track deviations
- Track outlier rate is defined as number of track updates with a deviation larger than 2 m in range or 2 m/s in velocity divided by the total number of track updates. This outlier threshold corresponds to the maximal possible measurement uncertainty in good detection conditions.

In Fig. 4 and Fig. 5 track error, outlier rate and the radar parameter settings are shown for the series TA1-TA6 for both the bicycle and the buggy target. For both targets, the velocity track error and the outlier rate increase while the needed time effort $T * D$ decreases, in line with the current objectives weight settings. However, the target size and dynamic behavior leads to different tracking performance. While the bicycle target has been tracked without any outliers and with every weight settings, only an optimization with a focus on "T" (TA1 - TA3) leads to a good tracking performance with the agile and small buggy target.

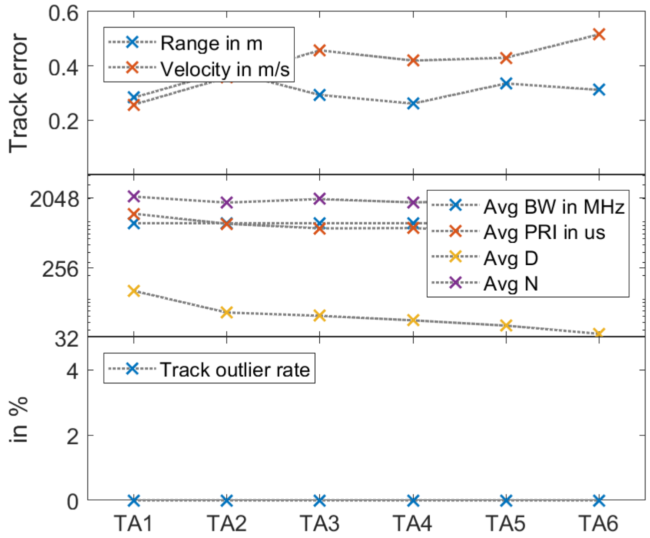

Fig. 4. Radar parameters and radar performance with the cases TA1 to TA6 and with the bicycle target. Panels from top to bottom: Track error in range and velocity; averaged radar parameters ; track outlier rate

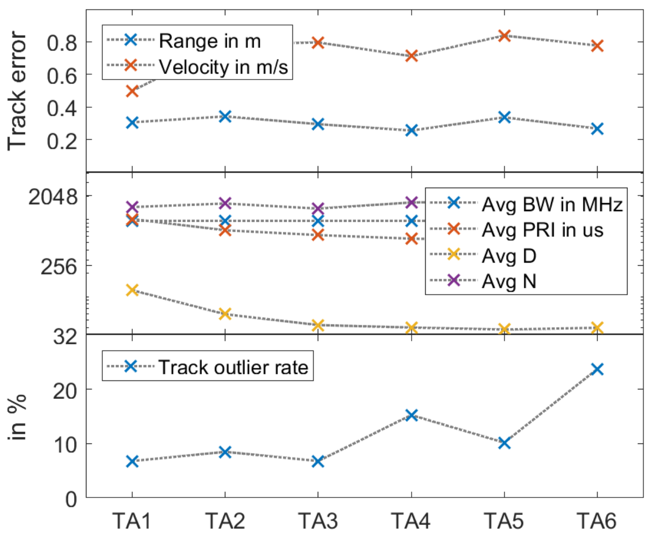

Fig. 5. Same as Fig. 4 but with the buggy target.

B. *Minimal bandwidth versus track accuracy*

Analogous to Sect. IV.A we consider in this section the joint optimization of track accuracy and bandwidth usage in

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scenario 2). In measurement BA1, the track accuracy is prioritized while at BA5, the focus is on bandwidth minimization. The effect of prioritization shifting from BA1 to BA5 on the tracking performance is demonstrated in Fig. 6 and with the bicycle target. If the focus is on track accuracy (weight set BA1, top panel), the scatter of the range measurements around the ground truth values is well below 0.5 m and the track deviates from the ground truth with not more than ~0.3 m. At the other end of the scenario, with weight set BA5, the measurement scatter is larger than 1 m and the corresponding track deviates go up to ~1 m.

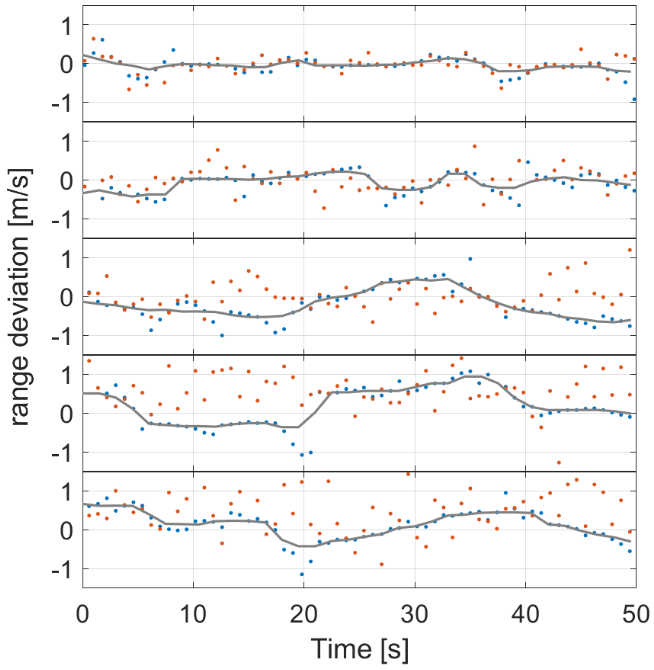

Fig. 6. Deviation of range measurements (red) and track (blue) updates with the BA1 (top panel) to BA5 (bottom panel) optimization and with the buggy target. The track updates are smoothed with a sliding window (grey line) for an indication of the track accuracy over time

In Fig. 7 and Fig. 8 we show the track error, outlier rate and radar parameter selection for the weight sets BA1 to BA5 defined in scenario 2).

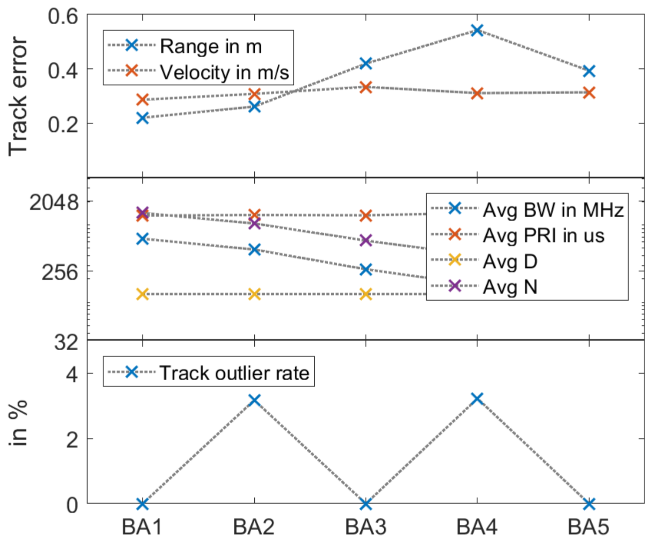

Fig. 7. Radar parameters and radar performance with the cases BA1 to BA5 and with the bicycle target. Panels from top to bottom: Track error; averaged radar parameters ; track outlier rate

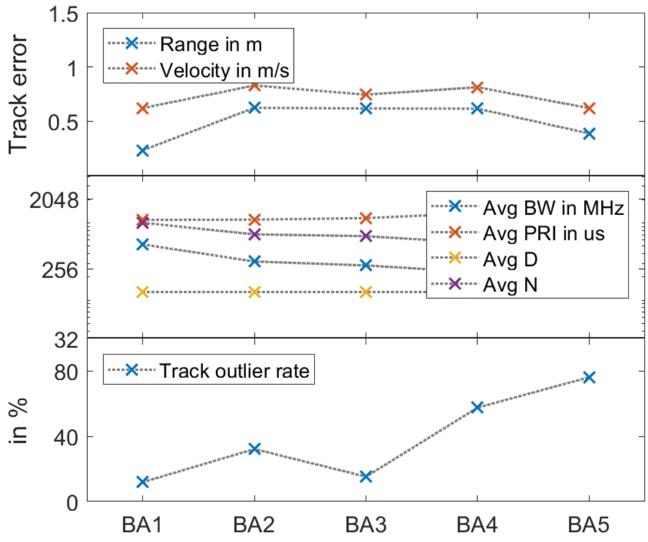

Fig. 8. Same as Fig. 7 but for the buggy target

Similarly to scenario 1) and with both the bicycle and the buggy target, the increase in track error and outlier rate correlates with a decrease of bandwidth usage. Contrary to the bicycle target (Fig. 7), the buggy target (Fig. 8) can only be tracked accurately with an objective weight set with a focus on tracking accuracy (BA1-BA3)

C. Target Comparison

Scenario 1) and 2) have also been used for measurements with the motor car and the lawn tractor. Similar optimization results and radar parameter selections have been found. However, the actual tracking results differ from one to the other target as a result of the different target size and dynamic behavior. While the bicycle can be tracked with every single objective weight set, only a weight set with focus on track accuracy (such as TA1 or BA1) is able to track the agile buggy target. On the other hand, the lawn tractor is easier to track, but the small target velocities leads to a loss in SNR due to the ground clutter MTI filter and thus to a large measurement and track uncertainty. Finally, the car target has multiple scattering centers and a large range and velocity spread in the RD plane which disturbs an accurate tracking.

V. Conclusion

In this work, detection and tracking experiments with the cognitive adaptation of waveform and processing parameters have been performed. Four target types with different backscatter and dynamic behavior have been used and the radar system has been optimized to different combinations of the three top-level objectives “track accuracy”, “bandwidth minimization” and “time effort minimization”.

We were able to demonstrate the optimization of waveform and processing parameters and the corresponding real-time adaptation of the sensor. The optimizer minimizes a generalized cost function that takes the required radar resources and the predicted track uncertainties into account.

The tracking performance with each target and objective weight setting has been analyzed by comparing the radar data to the DGPS ground truth data. The analysis shows that tracking performance correlates with the prioritization of the track accuracy goal over other top-level objectives. The

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radar performance and resource usage depends smoothly on the single objective weights used for the cost function parameterization. Thus, the system can be fine-tuned to one or to a combination of top-level objectives with a given prioritization. For example, a simultaneous minimization of bandwidth usage (Main objective, 1st prioritization) and track error (2nd prioritization) can be performed.

The results also show that the tracking performance is poor with the buggy target and with objective weights whose focus is not on track accuracy. The reason is the fixed tracking parameterization which is not suitable for the agile target dynamics of the buggy. To improve the track performance for such targets, adaptive track parameter can be used. An extension of the cost function and the optimization algorithm to adaptive tracker parameters is straight forward. The application of the perception-action cycle to optimize the tracker update time is considered in [5].

With the current testbed, we were able to demonstrate cognitive-inspired optimization based on the perception-action cycle in a limited experimental setup. Other degrees of freedom, such as code diversity (waveforms beyond LFM), spatial diversity (multi sensor environment) and other aspects of cognition, such as (machine) learning, planning and the use of external data sources are not considered. To assess the benefit of cognitive algorithms over rule-based adaptation schemes, a radar testbed with more degrees of freedom to optimize is needed. Plans to extend the current system to a multi sensor system with multitarget tracking/prioritization and radar resource management (RRS) is underway.

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