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Statistical Approach for Automotive Radar Self-Diagnostics

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***Abstract*— In this paper, the problem of on-the-fly estimation of the radar state (self-diagnostics) is considered. We propose to use repetitive objects of the road infrastructure, such as lampposts, for continuous diagnostics of the radar state. The selected approach allows accounting for the external factors, such as water layer or dirt on the bumper, which can significantly affect radar performance, but cannot be retrieved with the internal calibration. The statistical model for RCS of repetitive targets is considered, and the estimator of the actual radar gain from the received data is derived. It is demonstrated that observing a few tens of targets is sufficient to provide a reasonable estimation of the radar performance within the operational mode.**

***Keywords*— Self-diagnostics, Quality of Service, Automotive Radar, Calibration.**

I. Introduction

According to International Telecommunication Union Recommendation ITU-T E.800 "Definitions of terms related to quality of service" [1] the quality of service (QOS) is defined as the totality of characteristics of a telecommunications service that bear on its ability to satisfy stated and implied needs of the user of the service. Adapting this to the sensing tasks means analysis of sensors performance and operations means dominating user needs and user satisfaction over formal optimization of sensing performance. In the automotive application, user needs include safe and convenient motion from a departure point to the destination. This includes prevention of accidents and collisions with other traffic participants, making maneuvers with acceptable/convenient for passengers levels of acceleration. Within such a mission, sensors have to provide a reliable level of situation awareness - detect potential threatening targets at distances, which, accordingly to approach velocity, will provide enough time for car's control computer to decide on preventive measures (e.g., slow down and stop; make maneuver/react with a convenient level of acceleration).

Continuous changes in environmental and sensing conditions can affect the quality of radar measurements and make radar data non-reliable. The modern Advanced Driver Assistant Systems (ADAS) consider radar to be the main sensors for the surveillance awareness, together with the lidar and camera. The questions of how good the radar data is and of how much it can be trusted, then become crucial for the appropriate data association from multiple sensors.

Radar quality information has been considered in a few studies, aimed in the qualitative description of meteorological data [2], [3]. Despite different radar applications, some concepts of radar quality descriptions are applicable to any radar sensor. Thus, different factors bearing radar performance can be classified into global static, local static, global dynamic, and local dynamic descriptors. The global factors affect all data points, irrespectively to the range, angle, and velocity position, while the local factors depend on the target position and velocity. Static factors refer to the factors constant in time, while dynamic varies from one observation to another. With application to the radar state estimation, it implies that static and dynamic factors should be treated differently. Estimation and compensation of the static factors are treated by calibration while accounting for the dynamic factors is the aim of on-the-fly system state identification, also called self-diagnostics.

Two main approaches are used to describe the quality of the radar measurements:

1) Simulation of instrument and propagation errors;
2) Retrieval of errors by comparing the data with the ground truth.

In the first approach, uncertainty is simulated based on the error models and detailed knowledge about the sources of error, while in the second approach no assumptions of the origin of the error is made. The second approach is used for the stationary radars, for which the clutter map of the surrounding objects can be built and used for regular estimation of the radar quality measurements. With application to online state estimation of an autonomous car radar, both approaches have significant limitations. Rapidly changing scene of the radar makes it impossible to account for all sources of errors and propose a simple model to estimate radar QOS, neither it allows making an accurate map of the scene to perform the second approach.

In this paper, we propose to perform radar self-diagnostics using repetitive targets along the roads. The proposed processing allows detecting the degradation of the radar performance, and so of its QOS, which can be further used in the ADAS processor for improved data association from different sensors.

The rest of the paper is organized as follows: in section II approach of radar self-diagnostics is described and applicability of different objects as calibrating targets is analyzed. Then, in Section III the statistical approach for radar self-diagnostics is proposed. The performance of the method is evaluated in Section IV via numerical simulations. Finally, the conclusions are drawn in Section V.

II. Problem statement and selected approach

A. Problem statement

According to the radar equation:

$$P_r = \frac{P_t G_{proc} L_i \lambda^2}{(4\pi)^3} \cdot \frac{G_t G_r L_e}{R^4} \cdot RCS, \tag{1}$$

the power of the received signal P_r depends on the transmitted power P_t, the target radar cross-section (RCS), the range to the target R and the wavelength λ. It is also proportional to the gains of transmitting and receiving antennas G_t, G_r and to the signal processing gain G_{proc}.

The losses in (1) are implicitly divided into two groups, namely internal L_i and external L_e losses. The internal losses account for the factors arising in the physical block of the radar, which can be retrieved with a test signal and compensated in the data processing. The majority of modern radars (including automotive ones) schedule time slots for such testing, thus providing up-to-date estimation of the internal losses within their operational time, e.g. [4].

The external losses L_e, on the other hand, account for the changes of the propagation medium e.g. due to the variation of the weather conditions (rain, fog, snow), radom condition (water, dirt, ice layer on the radom), interference from other sensors, etc. These factors can significantly affect the radar performance (see e.g. [5]) but can not be defined a priori. In order to predict radar performance in its operational mode, or, in other words, to accomplish radar self-diagnostics, the impact of the external factors has to be retrieved from the data within radar operational time.

Assume the radar operates with a fixed set up, then we can write (1) as:

$$P_r(i) = G \frac{L_p(R_i) G_{t,r}(\theta_i)}{R_i^4} RCS_i = G g^2(R_i, \theta_i) RCS_i, \tag{2}$$

where G represents the global factors in (1) (up to a constant). The local factors are considered via the function $g(R, \theta)$, which depends on the i-th target location R_i and θ_i (in 2D polar coordinates) via the antenna pattern $G_{t,r}(\theta_i)$, prorogation function $L_p(R_i)$ and range relation (R_i^{-4}).

Given the model (2), radar self-diagnostics can be established as an estimation of the global factors G from the radar measurements and comparing it to that of well-operating radar G_0 via:

$$Q = h\left(\frac{G}{G_0}\right), \tag{3}$$

where $h(\cdot)$ is some non-decreasing function. The estimation of the local factors can provide more insight into the radar performance, hence it would require performing the approach described below in a few non-overlapping subspaces of the range/angular domain simultaneously. The presence of calibrating targets in each subspace is difficult to ensure.

The conventional calibration procedure consists of estimation of parameter G, assuming all the other terms in (2), namely the function $g(R, \theta)$, target location (R_i, θ_i) and its RCS, are known.

B. Calibrating targets

A standard calibrating target (corner reflector, sphere, metal plate) has deterministic RCS, which for a given frequency can be found analytically, depending on its shape and size [6]. The application of corner reflectors, Luneberg lenses and phase-conjugate mirrors for automotive radar application, has been recently discussed in [7], [8]. Such reflectors can be installed into the existing road infrastructure (e.g. as a cat′s eye pavement markers [7]) and provide high RCS with low variation over wide observation angles. The major limitation of such targets is their installation and maintenance cost [8].

An alternative solution, considered in this paper, consist of using repetitive objects, already present in the road infrastructure as calibrating targets for radar self-diagnostics within operational time. The most often appearing targets along the roads are the traffic signs. The complicated geometrical shape of a traffic sign implies sufficient variation of its RCS with the aspect angle [9], [10], which has to be accounted if such targets are considered for self-diagnostics. The alternative solution is to use lampposts installed along the roads as calibrating targets. The lampposts have simple geometrical shapes at the observed elevation angles (cylinder circle or prism with octagonal base) and regular appearance along the highways (the distance between adjacent lampposts in the surroundings of Delft is 30-70 m, measured by Google maps).

Even though lampposts have simple shapes, they are not designed for radar calibration. Therefore, their RCS can vary from one to another due to mass production tolerances, installation etc. In order to account for this phenomenon, we propose to consider the RCS of such targets, to be used for radar self-calibration, not as deterministic values, but as a random quality, whose PDF is a priori known (or has been measured beforehand).

In this study, we consider that one class of targets is used for radar self-diagnostics, and their locations are known by a digital map (see e.g. [11]). We assume that RCS of the targets in this class follow non-central chi-squared distribution with two degrees of freedom, which provides sufficient fidelity for target RCS variation and encompasses Swerling models as particular cases [6] (approximately for Swerling III/IV target [12]).

III. Statistical approach for radar self-diagnostics

According to the definition above: $RCS \sim \sigma_A^2 \chi_2^2(\frac{A_0^2}{\sigma_A^2})$, which implies that the observed target magnitude follows Rice (Rician) distribution $|a| \sim \mathrm{Rice}(A_0, \sigma_A^2)$, where A_0 is the magnitude of the non-fluctuation target response and σ_A^2 is the variance of the disperse component. Assume the calibrating target with index i is detected by the radar at the location (R_i, θ_i). In the noise-limited scenario, the complex received signal (after pre-processing) in the range-angular cell with the target i is given by:

$$\begin{aligned}\tilde{y}_i = \sqrt{G} g(R_i, \theta_i) a e^{i\phi} + n_i = \sqrt{G} g(R_i, \theta_i) A_0 e^{i\phi} \\ + \sqrt{G} g(R_i, \theta_i) n_A + n_i = y_i e^{i\psi},\end{aligned} \tag{4}$$

where $\phi, \psi \sim U(0, 2\pi)$ are random phase terms, n_i is zero mean white Gaussian noise $n_i \sim \mathcal{CN}(0, \sigma_n^2)$ with the power being estimated from the data or defined as $\sigma_n^2 = k_{\text{B}} T_0 F B$ [6], with k_{B} being Boltzmanns constant (1.38×10^{23} watt-sec/K), T_0 — the standard temperature (290 K), F — the noise figure and B — the instantaneous receiver bandwidth.

Accordingly, the magnitude of the observed signal $y_i = |\tilde{y}_i|$ follows Rice distribution with parameters:

$$y_i = \text{Rice}\left(Cg(R_i,\theta_i)A_0,\ C^2 g^2(R_i,\theta_i)\sigma_A^2 + \sigma_n^2\right), \qquad (5)$$

where $C = \sqrt{G}$. Define simplified notations $u_i = g(R_i, \theta_i)A_0$ and $v_i = g^2(R_i, \theta_i)\sigma_A^2$, then the likelihood function for N independent measurements of calibrating targets $\mathbf{y} = [y_1, \ldots, y_N]^T$ is given by:

$$\begin{aligned}\Lambda\left(\mathbf{y}|C\right) = \prod_{i=1}^{N} f\left(y_i|C\right) = \prod_{i=1}^{N} \frac{y_i}{C^2 v_i + \sigma_n^2} \\ \cdot \exp\left(-\frac{y_i^2 + C^2 u_i^2}{2\left(C^2 v_i + \sigma_n^2\right)}\right) I_0\left(\frac{y_i C u_i}{C^2 v_i + \sigma_n^2}\right),\end{aligned} \qquad (6)$$

where $I_n(\cdot)$ is the modified Bessel function of the first kind with order n. Given the data model, the parameters C (or equivalently G) should be estimated from the observed data.

Note that the observed data set $\mathbf{y}$ is described as a mixture of Rice distributions with the parameters, given in (5), therefore C cannot be extracted by the method of moments or standard maximum likelihood estimator of the Rice distribution parameters [13].

Therefore, we perform maximum likelihood estimation of $\hat{C} = \text{argmax}_C \Lambda\left(\mathbf{y}|C\right)$ from (6). It is obtained as non-zero solution of:

$$\begin{aligned}C \cdot \sum_{i=1}^{N} \frac{u_i^2 \sigma_n^2 + v_i\left(2v_i C^2 + 2\sigma_n^2 - y_i^2\right)}{\left(C^2 v_i + \sigma_n^2\right)^2} \\ -\sum_{i=1}^{N} B\left(\frac{y_i C u_i}{C^2 v_i + \sigma_n^2}\right) \frac{u_i y_i\left(\sigma_n^2 - C^2 v_i\right)}{\left(C^2 v_i + \sigma_n^2\right)^2} = 0,\end{aligned} \qquad (7)$$

where $B(x) = \frac{I_1(x)}{I_0(x)}$ can be approximated by $B(x) \approx e^{-\frac{1}{2x}}$ for high values ($x > 5$), which is equivalent to dominant coherent target component and high SNR. The solution has to be performed numerically. We implemented it via NewtonRaphson method.

Consider two special cases: constant RCS target model (Swerling 0) and diffuse target model (Swerling I/II). Swerling 0 targets has $\sigma_A = 0$ and $v_i = 0, \forall i = 1, \ldots, N$, which allows to simplify (7) to:

$$\hat{C} = \frac{\sum_{i=1}^{N} B\left(\frac{y_i \hat{C} u_i}{\sigma_n^2}\right) u_i y_i}{\sum_{i=1}^{N} u_i^2}. \qquad (8)$$

For high SNR targets $B\left(x\right) \approx 1$. If all the measurements are collected from observing the same target at the fixed location, then $u_i = \text{const}, \ \forall i$ and the procedure degenerates to the standard calibration with averaging of multiple measurements.

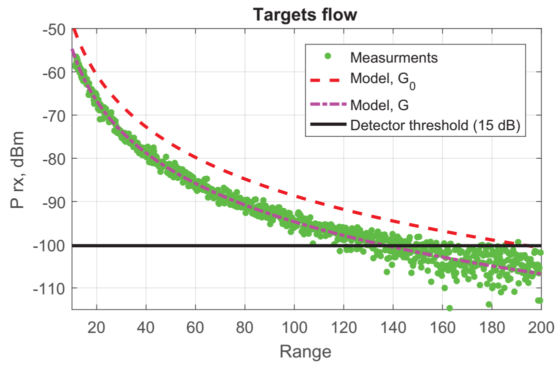

Fig. 1. Measured received power of calibrating targets, aligned with the range dependency for well-operating radar ($G = G_0$) and for the current state ($G = G_0/2$)

In case of the diffuse target model (Swerling I/II), $A_0 = 0$ and $u_i = 0, \forall i = 1, \ldots, N$, which gives the estimation of C^2:

$$\hat{C}^2 = \sum_{i=1}^{N} \frac{y_i^2 v_i - 2\sigma_n^2 v_i}{\left(\hat{C}^2 v_i + \sigma_n^2\right)^2} \Bigg/ \sum_{i=1}^{N} \frac{2v_i^2}{\left(\hat{C}^2 v_i + \sigma_n^2\right)^2}. \qquad (9)$$

Given the estimation of C (or equivalently $C^2 = G$) from the data, statistical self-diagnostics consists of comparing it to the true value by means of (3). It is assumed that the radar parameters are changing slowly with time. Therefore, the estimation of $\hat{C}$ is obtained from tens or hundreds of calibrating targets and multiple measurements of each target with the predefined update rate of the radar.

IV. Simulations

For the simulation herein we assume an automotive radar operating at $f_c = 76.5$ GHz with an array of $P = 12$ antennas with a half-wavelength spacing between each other. The coherent bandwidth is $B = 150$ MHz, which provides $\delta_R = 1$ m and the other parameters in are set in such a way that $P_r(R_{\max})/\sigma_n^2 = 15$ dB for $RCS_0 = 1$ m^2 by (2) for $R_{\max} = 200$ m. Moreover, for the considered distance, we assume negligible attenuation in the signal in the air $L_p(R_i)$ for the distances $R \leq R_{\max}$ (according to [6], at f_c attenuation in air is less than 1 dB/km for dry conditions and reasonable rain rates).

The simulator consists of the following blocks:

- Simulation of the scene with the calibrating targets on the right side of the car path with the distance of $d \sim \mathcal{U}(20, 30)$ m between them along the path and at displacement $b = 10$ m to the right from the path. The targets are assumed isotropic, RCS varies only from one target to another;
- The car is moving with $v_0 = 30$ m/s and all the calibrating targets detected within $\theta \in [-60, 60]$ deg and $R \leq R_{\max}$ are used for calibration;
- Targets $RCS \sim \sigma_A^2 \chi_2^2(\frac{A_0^2}{\sigma_A^2})$ and so $|a| \sim \text{Rice}(A_0, \sigma_A^2)$. Herein we set $A_0 = 1$ and $\sigma_A = 0.1$.
- It is assumed that calibrating targets are confirmed by the digital map, which includes markers of such targets;

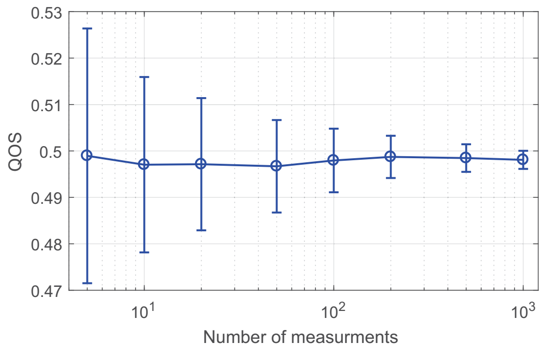

Fig. 2. Estimation of Q vs the number of calibrating targets

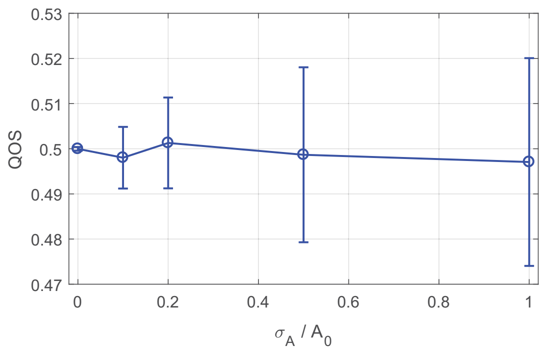

Fig. 3. Estimation of Q vs the distribution of target RCS

- Self-diagnostics is performed by estimating C from (7) and the quality factor is estimated by $Q = \sqrt{G/G_0}$ (other metrics can be preferable to bound it to $Q \leq 1$).

An example of the received power from the observed calibrating targets as the function of their range is demonstrated in Fig. 1 for $L = 1000$ detection of the targets and $g(R, \theta) = R^{-2}$ (angle dependence is omitted for better visualization). Herein $Q = 0.5$ was set and the estimation obtained with (7) converges to the true value and shows about 30% degradation of the maximum detectable range, $\hat{R}_{\max}$. The evaluated $\hat{Q}$ or the adjusted maximum range will be delivered to the ADAS, where it can be considered for situation awareness or fusing radar data with information from the other sensors.

The impact of the number of calibrating targets, considered for the radar self-diagnostics is demonstrated in Fig. 2 for the targets and radar parameters, mentioned above, averaged over 100 test. The result demonstrates the decreasing variance of the estimation $\hat{Q}$ with more targets, used for calibration.

The impact of the target PDF on the estimation of Q is evaluated in Fig. 3 for $N = 100$. Notably, the variance of the estimator decreases when the target RCS is known ($\sigma_A = 0$) and diverges when σ_A increases. However, the variation is only of a few percents for large variations of the targets PDF.

V. Conclusion

In this paper, we proposed a method for continuous evaluation of the automotive radar state by evaluating the responses for repetitive objects along the road. The proposed approach allows accounting for the slow changes of the radar state within its operational time, to be considered in the further stages of data processing. Given a few tens of calibrating targets, the estimated radar gain is within ten percent from the actual one, even with a moderate variation of the targets RCS. The future work will be devoted to the extension of the approach for more general classes of distributions for targets RCS and also accounting for a few classes of targets embedded in the road infrastructure.

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