Unsupervised Online Horizontal Misalignment Detection Algorithm for Automotive Radar

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***Abstract*—This paper proposes a stationary target based online unsupervised calibration algorithm that can be applied on both 4D and 3D automotive radars for its horizontal alignment and misalignment detection. The calibration process requires no special EOL (End of Line) setup or stationary structures of reference. The method is based on the accurate determination of the own vehicle velocity and by using stationary targets. The approach provides both a long-term stable azimuth mounting compensation value as well as a separate, more dynamic angle value that converges faster than the long-term value in case of small accidents. The proposed method considers the systematic errors resulted from the vehicle integration and bumper tolerances and delivers an accurate horizontal alignment correction by using filtering outlier rejection techniques. The performance is evaluated used real world data from drive tests executed with a 77 GHz series automotive radar, showing promising results.**

Keywords*—*Automotive Radar, azimuth calibration, automatic calibration, ADAS, AD

I. INTRODUCTION

For Automated Driving (AD) systems, one important challenge is the accurate environmental perception by the sensors that are encompassed by these systems. One such system is the automotive radar. The radar has active functionalities like LCA (Lane Change Assist), CTA (Cross Traffic Alert) or TA (Turn Assist), that require precise detection and ranging of the traffic and the environment due to the active monitoring and potential danger assessment in the scope of delivering warnings for the driver. An error in the sensor alignment can pose a serious risk in the radar target, object, and environment detection, decreasing the perception accuracy and overall performance of the system [1]. The main cause for the angular distortions is the mounting angle errors from the vehicle manufacturer’s plant. There are offline calibration methods, which take place in the customer's automotive production plant or in service (End Of Line Calibration).

These involve placing the vehicle in a well-defined set-up together with various reference objects whose attributes such as position and angles of azimuth and elevation are well known, respecting strict tolerances [2]. These methods are disadvantageous both financially and in terms of the time required to perform the calibration of a vehicle, while also not ensuring the correct and stable compensation during the lifetime of the sensor, mainly caused by the aging of the electronics, vibrations due to driving, bumps in the road or even small accidents. Therefore, the online calibration methods are preferred: these methods are continuously tunable and adjustable and can adapt on any vehicle, while driving. The approach in [3] calculates the misalignment angle based on two pairs of range and azimuth angle continuous measures of the same stationary target. A disadvantage of this method the difficulty of tracking the same radar target over multiple measurement cycles, while also having the assumption that there is only a small misalignment. The method proposed by Guo et al. [1] requires a straight stationary reference (guardrail) and performs a line fitting from the targets around it, obtaining a misalignment angle from the slope. This method works only in the presence of a stationary reference. Kellner et al. [4] make use of gyroscope and radar motion estimation algorithms to calculate the lateral velocity of the sensor in low yaw rate scenarios, in order to determine the misalignment angle. In [5], the method used calculates the joint azimuth-elevation misalignment from the vehicle velocity, the side-slip-angle, and its own target measurement. The misalignment angle is then calculated by feeding the data to a recursive filter or by batch processing it. Lastly, in [6] Bao et al. propose a procedure where the mounting angles for azimuth and elevation are calculated without knowing the radar position.

The objective of the paper is to introduce an online unsupervised azimuth calibration algorithm for the automotive radar. The main contributions of the paper are:

- A fully functional model that can adapt the radar system to the azimuth mounting error.
- The usage of two correction values (robust and dynamic values) resulted from two different sets of 1D Kalman filtering parameters. The robust value will describe the stable, overall global compensation angle, while the dynamic value will be used to detect sudden changes, such as accidents. A hysteresis will be used to choose which value is used to correct the radar raw targets.
- A method to accurately determine the horizontal alignment angle despite the influences of the vehicle integration and bumper over the azimuth angle of arrival, in case of a lack of existing correction table or inaccurate individual correction values [7], [8].

The remainder of paper is organized as follows. Section II presents the calibration procedure. Section III and IV elaborate on the types of filtering (robust vs dynamic) used and outlier rejection method in the case of bumper influences on the stationary targets.

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II. THE AUTOMATIC CALIBRATION MODEL

Considering the scenario from Fig.1 the vehicle is driving straight (at a very low yaw rate), and thus, will not present lateral velocity. The algorithm will use only suitable stationary targets. The target suitability can be decided by factors such as relevant relative distance, angular interval in azimuth and in elevation (for 4D radars), signal-to-noise ratio and others.

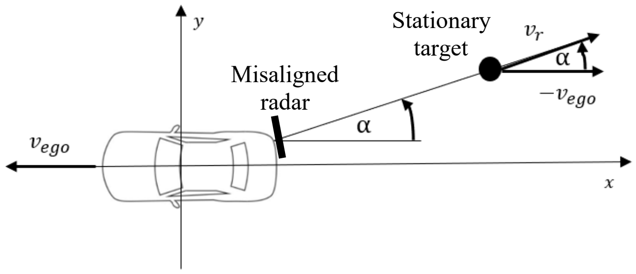

Fig. 1. Scenario for the estimation of the real target angle.

For calculating the horizontal alignment angle, the following inputs are required: the vehicle velocity v_{ego}, the measured target velocity $\widetilde{v_r}$ and the measured azimuth angle of the target, $\tilde{\alpha}$. In the case of a straight driving scenario, the stationary targets would be seen as having the same longitudinal velocity as the ego vehicle, but with the opposite sign, meaning $v_{r,x} = -v_{ego}$. This can be rewritten as:

$$\widetilde{v_r} \cong -v_{ego} \cdot \cos(\alpha) \tag{1}$$

where α is the reference azimuth angle. We can easily calculate α from (1), in the following way:

$$\alpha = \arccos\left(-\frac{\widetilde{v_r}}{v_{ego}}\right) \tag{2}$$

The measured angle $\tilde{\alpha}$ can be described as:

$$\tilde{\alpha} = \alpha + \varepsilon_h + \eta_\alpha \tag{3}$$

where ε_h is the horizontal angular mounting error and η_α is white Gaussian noise. Therefore, the measured angle correction value for a valid target is:

$$\widetilde{\Delta\alpha} = -\varepsilon_h - \eta_\alpha = \alpha - \tilde{\alpha} \tag{4}$$

For an accurate estimation, a filtering method needs to be applied due to the measurement noise and the low yaw rate values that still impact the estimation. In this paper, we propose the usage of a 1-D Kalman filtering method [9], where we consider predicting only the covariance, as shown in equations (5) to (9).

$$\widehat{\Delta\acute{\alpha}}_{k+1} = \widehat{\Delta\alpha}_k \tag{5}$$

$$\acute{P}_{k+1} = P_k + Q \tag{6}$$

$$K_k = \frac{\acute{P}_k}{\acute{P}_k + R} \tag{7}$$

$$\widehat{\Delta\alpha}_k = \widehat{\Delta\acute{\alpha}}_k + K_k \cdot (\widetilde{\Delta\alpha} - \widehat{\Delta\acute{\alpha}}_k) \tag{8}$$

$$P_k = (1 - K_k) \cdot \acute{P}_k \tag{9}$$

where $\Delta\alpha$ is the horizontal correction value, P is the estimate error covariance, K is the Kalman gain, Q is the process noise covariance, R is the measurement noise covariance, ´ represents the a priori state estimate at step k (without the symbol ´ it represents the a posteriori state estimate).

III. PURPOSE-BASED CORRECTION FILTERING

During the lifetime of the sensor, it is important to have a steady and stable calibration value that can provide an overall long-term electronic compensation of the sensor misalignment. To achieve a stable and accurate calibration value, the algorithm should use a slower adaption. In critical situations, like accidents, when the bumper is hit, thus creating a misalignment of the sensor, it is very important that the algorithm converges in a fast manner to the new compensation value. For this, a quicker, more dynamic adaption should be used, while expecting a relatively lower accuracy than the robust filtering method.

In order to achieve the above-mentioned points, we propose to compute the robust and dynamic angle by using two different sets of Kalman filtering parameters Q and R, with a set of higher valued parameters for the dynamic angle correction $\Delta\alpha_d$, and a lower valued set of parameters for the robust angle $\Delta\alpha_r$, respectively.

The correction value $\Delta\alpha_u$ that will be used for the misalignment detection and target correction is described in (10):

$$\Delta\alpha_u = \begin{cases} \Delta\alpha_r, if\ c < h_{min} \\ \Delta\alpha_d, if\ c > h_{max} \\ previous\ state\ used, if\ c \in [h_{min}, h_{max}] \end{cases} \tag{10}$$

where $c = |\Delta\alpha_r - \Delta\alpha_d|$, h_{min} and h_{max} are the minimum and maximum required absolute differences for the hysteresis trigger.

IV. SECTOR-BASED ANGLE CALIBRATION

Automotive radar sensors are usually mounted behind bumpers, which can lead to performance degradation of the angle measurement due to properties like paint, coating, shape, and material. The angle measurements are affected by errors from multipath propagation, refraction, diffraction and reflections of the signal depending on the angle of the incident wave. In this paper, we will refer to these systematic distortions as local offsets.

Considering the local offsets, the measured angle from (3) becomes:

$$\tilde{\alpha} = \alpha + \varepsilon_h + \varepsilon_{sys}(\alpha) + \eta_\alpha \tag{11}$$

where $\varepsilon_{sys}(\alpha)$ is the systematic individual error.

In order to minimize the systematic error $\varepsilon_{sys}(\alpha)$, a local correction $\Delta_{\alpha_{sys}}(\alpha)$ must be applied to the measured angle and (4) becomes:

$$\widetilde{\Delta\alpha} = \alpha - \breve{\alpha} \tag{12}$$

where $\breve{\alpha} = \alpha + \varepsilon_h + \varepsilon_{sys}(\alpha) + \Delta_{\alpha_{sys}}(\alpha) + \eta_\alpha$.

In ideal situations, $\varepsilon_{sys}(\alpha) \cong -\Delta_{\alpha_{sys}}(\alpha)$, cancelling each other. However, in non-ideal cases, if the local errors $\varepsilon_{sys}(\alpha)$ are not fully compensated by $\Delta_{\alpha_{sys}}(\alpha)$, the uncompensated local angular offsets will be incorporated inside the estimated horizontal correction. Our proposed method involves splitting the relevant azimuth angular interval in a number of N angular sectors and estimating $\Delta\alpha_u$ for each angular sector individually, for every radar cycle k, as in (13):

$$\boldsymbol{\Delta\alpha_u} = [\Delta\alpha_{u0}\ \Delta\alpha_{u1} \dots \Delta\alpha_{uN-1}]^{\mathrm{T}} \tag{13}$$

The sector i attributed to the measured correction value is calculated as follows:

$$i = \left[\frac{\alpha - \alpha_{start}}{\alpha_{step}}\right] \tag{14}$$

where $\alpha_{step} = \alpha_{end} - \alpha_{start}$ is the sector angular interval, α_{start} and α_{end} are the minimum and maximum azimuth angles allowed for the target selection criteria.

Ideally, the distribution of the measured correction value $\widetilde{\Delta\alpha}$ should resemble a Gaussian distribution with the mean value equal to the true correction value. However, several angular sectors might be affected by either the systematic local offsets in case of not using any local correction measures, or the local corrections are not accurate enough, thus skewing the normal distribution. By using outlier rejection methods, we will remove the most affected angular sectors from the estimation of the correction angle.
For the outlier rejection process, we compared the performance of three types of methods: median absolute deviation, standard deviation [10] and generalized extreme Studentized deviate (gesd) tests for outliers [11].

V. Numerical Results

In this section we present the simulation results for the proposed method. The algorithm is tested with a commercial millimeter wave automotive radar that has the following features: centre frequency of 76.5 GHz, azimuth and elevation angle field of view of ±80°, respectively ±10°, high resolution in distance, relative velocity and angle, ethernet communication interface. The results are based on real data from different test drives effectuated on a highway, in optimal driving and environmental conditions for a rear left radar sensor. This data is used as input for our simulation environment and the local offset errors caused by the bumper influence have been compensated.

Fig. 2 and Fig. 3 illustrate the robust and dynamic horizontal alignment corrections along with the histograms of correction values, for a sensor that presents no azimuth mounting errors ($\varepsilon_h \cong 0$). Both filtering methods provide an estimation mean value centered around 0° (-0.034° for robust filtering vs -0.032° for dynamic filtering), while the dynamic filtering has a higher variance than the robust filtering method (0.016° for robust filtering vs 0.0289° for dynamic filtering).

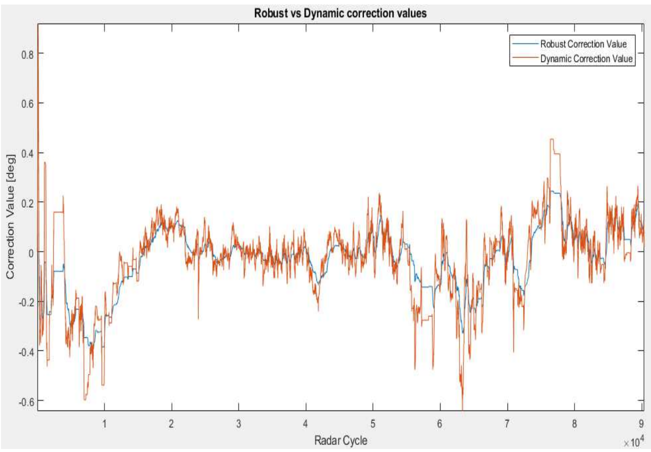

Fig. 2. Horizontal correction for 0° scenario.

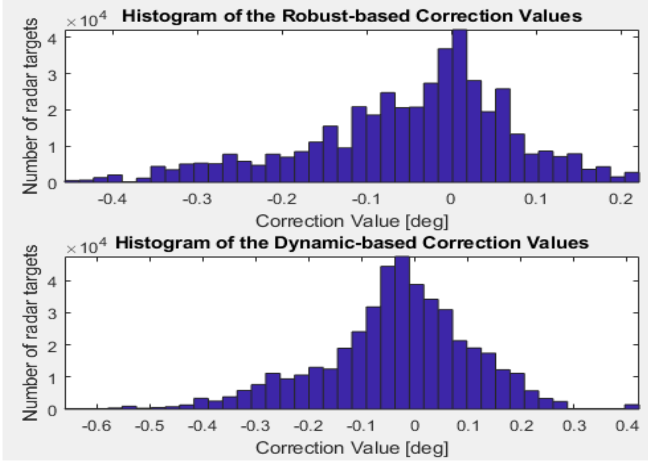

Fig. 3. Histograms of the correction values for 0° scenario (upper: robust vs lower: dynamic filtering).

In the second misalignment scenario, starting from the initial simulation, after 8000 radar cycles we added an artificial misalignment offset of 6° for the purpose of simulating the effect of a possible accident that would hit the bumper in such way that the azimuth mounting angle of the sensor would be changed. Fig. 4 demonstrates the efficiency of the dynamic filtering compared to the robust filtering from the point of view of the time required to converge to the new misalignment correction.

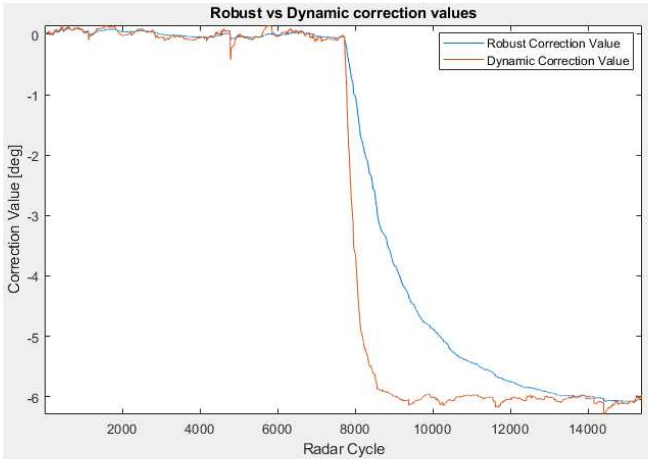

Fig. 4. Horizontal correction for 6° error scenario (second scenario).

In the third scenario, we show the effect of the local offset errors $\varepsilon_{sys}(\alpha)$. The radar sensor mounted behind the bumper is affected by uncompensated local offsets in a certain angular interval (55°-75°). Fig. 5 shows the ideal azimuth local correction curve for which the local offsets would not affect the estimation (first scenario), compared to the correction curve used in this scenario.

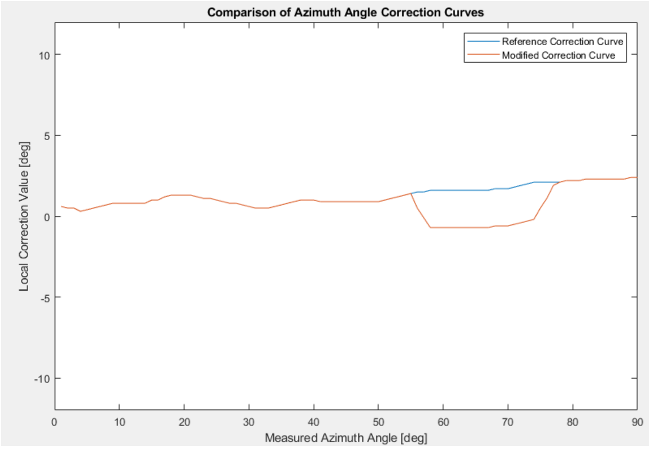

Fig. 5. Comparison between the used versus ideal azimuth correction curves for the sensor used in the test drive (scenario 3 vs 1).

Fig. 6 presents the resulting dynamic and robust horizontal corrections for the third scenario. As opposed to the first scenario (Fig. 2 and 3), the mean values are no longer centered around 0°, exhibiting a positive offset, due to the cumulated influences of the uncompensated local errors.

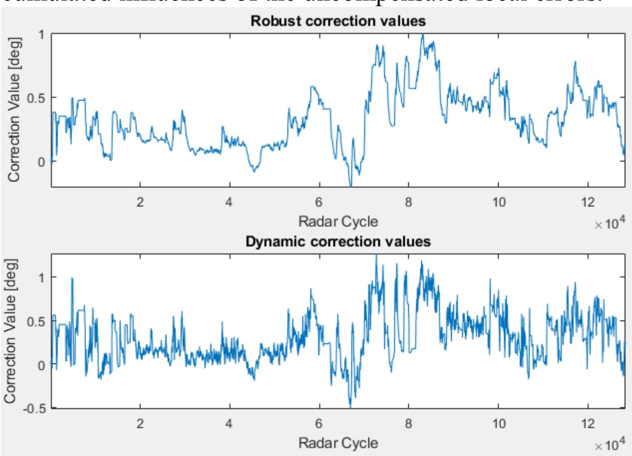

Fig. 6. Horizontal correction for 0° scenario with suboptimal angle correction curve (scenario 3).

Fig. 7 illustrates the histogram of the correction values for third scenario. Due to the impact of the uncompensated local errors, the histogram is now skewed to the right side.

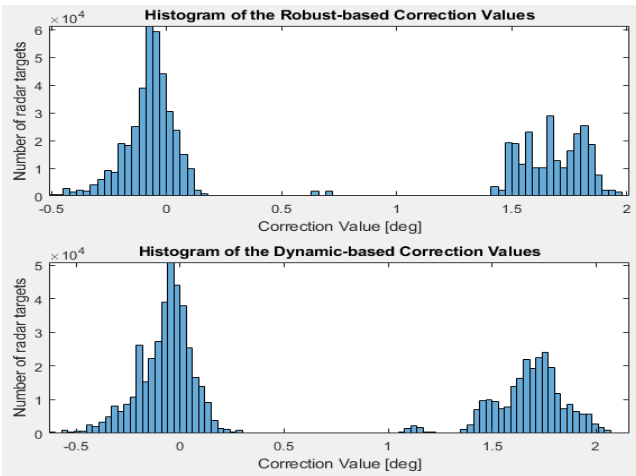

Fig. 7. Histograms of the correction values for 0° scenario (upper: robust vs lower: dynamic filtering, scenario 3).

To minimize the influence of the local errors, the method implies splitting the relevant azimuth angular interval in N = 5 angular sectors and estimating $\Delta\alpha_d$ and $\Delta\alpha_r$ for each sector individually. In Fig. 8, the comparison between the misalignment correction values from Fig. 6 and the correction values calculated for each angular sector are presented. The values influenced by the local errors are present in sectors 3 and 4.

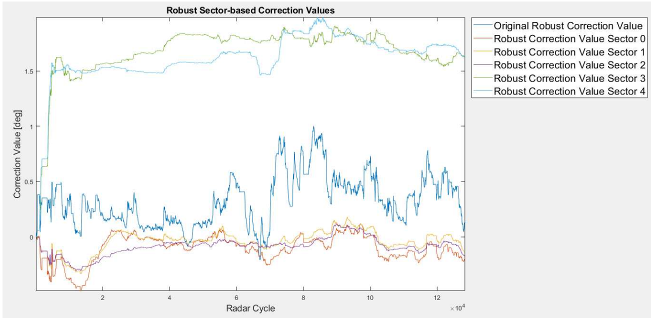

Fig. 8. Comparison of sector-based horizontal correction values.

In order to determine the outlier sectors and best misalignment correction value, several outlier rejection methods were used. Fig. 9 presents the recalculated horizontal alignment correction values after the outlier rejection procedure for the following thresholds:

- three scaled median absolute deviations (MAD) away from the median,
- one standard deviation away from the mean,
- detection threshold of 0.2, for the generalized extreme Studentized deviate test.

The median based method exhibits the most stable and accurate results, while the standard deviation method was unable to reject the outlier correction values at all moments in time.

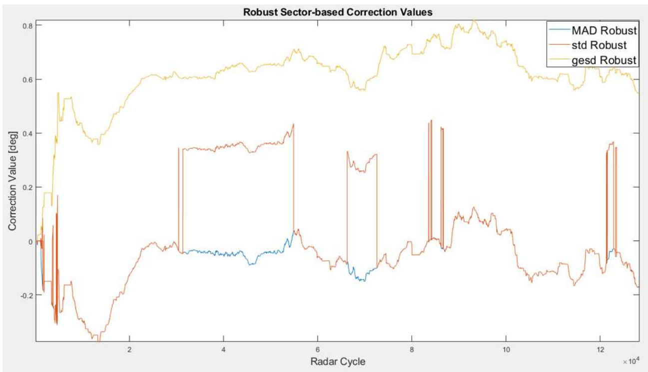

Fig. 9. Comparison of resulted correction values after outlier rejection.

TABLE I. Comparison Of The Resulted Correction Values For Scenario 3

Correction Method	Mean Value [°]	Variance [°]
Initial $\Delta\alpha_r$	0.323	0.048
Initial $\Delta\alpha_d$	0.303	0.078
MAD Based $\Delta\alpha_r$	-0.034	0.008
MAD Based $\Delta\alpha_d$	-0.024	0.014

Fig. 10 presents the differences between the initial robust correction values for scenario 3 and the median based robust correction value obtained after the outlier rejection process.

The misalignment correction value based on the outlier rejection method provides an estimation mean value centered around 0, while the initial method has a more inaccurate mean value and a higher variance, as seen in Table I.

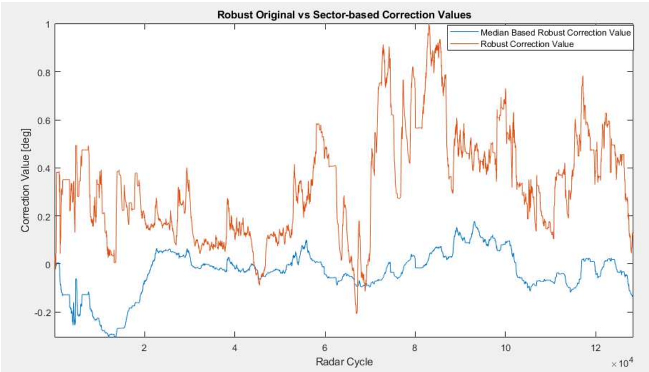

Fig. 10. Comparison of correction values before and after outlier rejection (scenario 3).

VI. Conclusions

In this paper, an ego velocity based unsupervised online calibration for estimating the horizontal misalignment of an automotive radar has been introduced. The method is based on stationary targets and uses two automatic calibration values based on different sets of values for the process and measurement noise, in such way that one value is stable and accurate on long-term driving scenarios, while the other value provides a faster misalignment detection in case of accidents. The proposed method provides accurate results in scenarios where the sensor is not adapted to the vehicle integration and bumper tolerances, by separating the relevant angular interval in equal azimuth sectors and estimating a pair of robust and dynamic correction values for each sector. The final value is then chosen based on the resulting suitable sectors left after an outlier removal procedure takes place.

The algorithm has been tested in a software in the loop (SiL) environment and shows promising results. Future work includes the extension of the method for a vertical alignment and misalignment detection.

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