Unsupervised Online Vertical Misalignment Detection Algorithm for Automotive Radar

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***Abstract*—This paper proposes a method for automatic detection and correction of the elevation mounting angle error of a 4D automotive radar integrated in a vehicle. The process requires no special calibration jig and can be used in such a way that it replaces the ordinary initial calibration methods; it also provides a continuous calibration during the lifetime of the sensor. Stationary targets reflected from the environment are used in a line fitting algorithm, for the purpose of calculating a vertical misalignment angle. The method provides a set of two correction values: a dynamic value that converges in a fast manner in case of small accidents and a more stable elevation correction value that converges slower and offers a long-term compensation value of the lifetime of the sensor. Real world data gathered from drive tests with a 77 GHz series automotive radar was used for the performance evaluation of the proposed method, showing promising results.**

Keywords—Automotive Radar, vertical misalignment, elevation calibration, automatic calibration, ADAS, AD

I. Introduction

Accurate environmental perception by the plethora of sensors that make up Automated Driving (AD) systems is their most difficult problem. One such sensor is the automotive radar. Due to active monitoring and risk assessment in the context of providing warnings for the driver, the radar offers active functionalities like Environment Detection, Cross Traffic Alert, or Lane Change Assist, that require precise detection and ranging of the traffic and environment. The detection of radar targets, objects, and environments can be compromised by a problem with the sensor alignment, which also affects the system's overall performance and perception accuracy [1]. Errors in the mounting angle from the plant of the car manufacturer are the primary cause of the angular distortions. This kind of error has been well studied in literature for azimuth [1-5]. However, in the last years, with the advancement of automotive radars with respect to elevation measurement, this information can be used with more confidence in object plausibilisation and perception, for a better classification or for other purposes, that include finding if the object is over-drivable or under-drivable. There are offline calibration techniques that are used in the customer's auto manufacturing facility or in service (End of Line Calibration).

Such methods require the placement of the vehicle in a set-up that is well defined, as well as necessitating reference objects, like metal poles or corner reflectors, with known attributes in terms of position, azimuth and elevation angles. In [6], a method of measuring elevational misalignment of an automotive radar sensor in a factory or service setting uses at least two targets positioned at different elevation angles and the misalignment is determined based on the ratio or difference in the return signal amplitude for the two targets. In [7], a method and an apparatus for aligning the elevation of automotive radar includes the positioning of at least three radar reflectors in a pattern in which the reflectors are fixed relative to one another, at different elevations and at least three different horizontal positions. Other methods that use calibration jigs are presented in [8-10]. These approaches are costly and time-consuming, and they do not ensure accurate and stable compensation over the sensor's lifetime. The main reasons for this are the aging of the electronics, vibrations from driving or heavy cargo in the trunk, potholes or even minor accidents, and the obvious difference between a vehicle (such as a truck) that is loaded or unloaded with materials. The online calibration methods, which should be perpetually tunable and capable of adapting on any vehicle, while driving, are therefore favored. The approach in [11] uses the vehicle's speed, side-slip angle, and its own target measurement to calculate the joint azimuth-elevation misalignment. The input is then processed in batches or by applying a recursive filter to determine the misalignment angle. The mounting angles for both azimuth and elevation are determined without knowledge of the radar position in [12], which is the last method Bao et al. suggest.

Our goal is to propose an online unsupervised elevation calibration algorithm for automotive radar. The following are the paper's main contributions:

- A fully functional model capable of adapting the radar system to elevation mounting angle error and serving as both an initial and ongoing calibration.
- Two separate sets of parameter combinations that led to the use of two correction values, robust and dynamic. The dynamic value will be utilized to identify rapid changes, such as in case of accidents, while the robust value will reflect the stable, overall global compensation angle. Which value will be utilized to correct the radar raw targets will be determined based on a hysteresis mechanism.

The remaining sections of the paper are structured as follows. The calibration process is presented in Section II. The usage of robust vs. dynamic filtering is discussed in more detail in Section III, and the numerical results are shown in Section IV. We provide the conclusions and some potential future study directions in Section V.

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II. THE AUTOMATIC CALIBRATION MODEL

In the case shown in Fig. 1, the car is traveling straight while in an appropriate environment (such as a highway), and radar reflections from stationary objects (such as a metal guardrail) show a vertical inaccuracy (ε_v) that is the result of the radar sensor's improper elevation mounting.

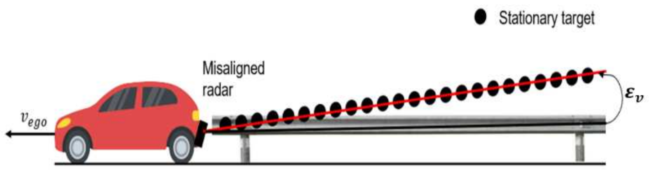

Fig. 1. Scenario for the estimation of the vertical correction.

For the calculation of the elevation misalignment angle, only suitable targets will be used. Selection factors such as raw target stationarity, longitudinal and lateral position, target height, angular elevation interval, signal-to-noise ratio (SNR), and others are used to determine the suitability of a target. The benefit of a rigorous target selection can be observed in Fig. 2.

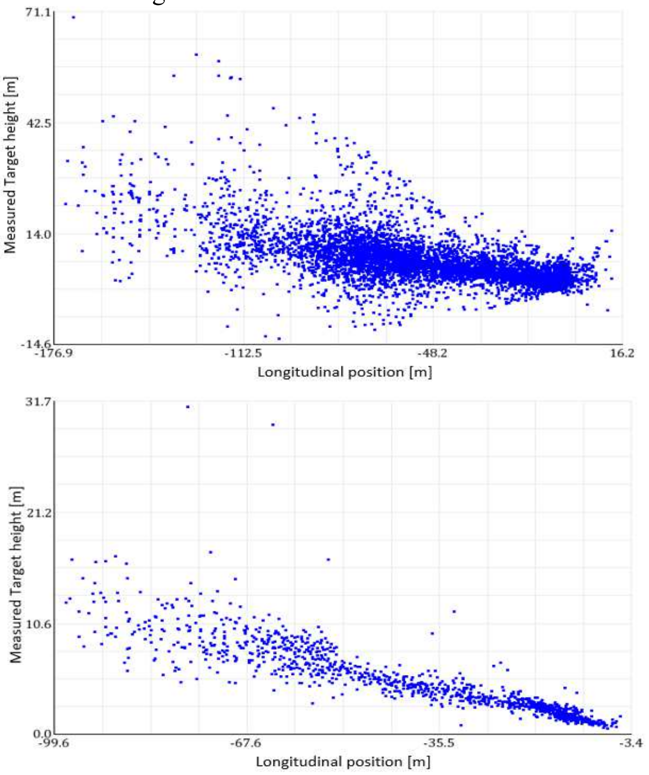

Fig. 2. Example of all targets from multiple consecutive radar cycles (upper picture) compared to the suitable targets used by the algorithm (lower picture) in the context of a misaligned radar in the elevation direction.

These targets can be used in a line fitting method like least squares regression, based on target longitudinal position and height, calculated in equations (1) and (2), to obtain an offset and a slope, then trigonometrically calculating the angle based on the slope of the resulted line:

$$\tilde{z} = \tilde{R} \cdot \sin\left(\beta + \varepsilon_\beta + \eta_\beta\right) \quad (1)$$

$$\tilde{x} = \tilde{R} \cdot \cos(\alpha), \quad (2)$$

where $\tilde{z}$, $\tilde{x}$ are the measured height and longitudinal position of the target, $\tilde{R}$ is the measured distance of the target, α is the azimuth angle, β is the elevation angle, ε_β is the vertical mounting error and η_β is Gaussian noise.

However, storing and executing the least squares regression on that many pairs of longitudinal positions and heights can be too demanding in an automotive system, where memory and runtime requirements are very tight.

Our proposed method indicates the splitting of the longitudinal axis into equidistant bins, as seen in Fig. 3 and each target will be attributed to its bin, according to equation (3):

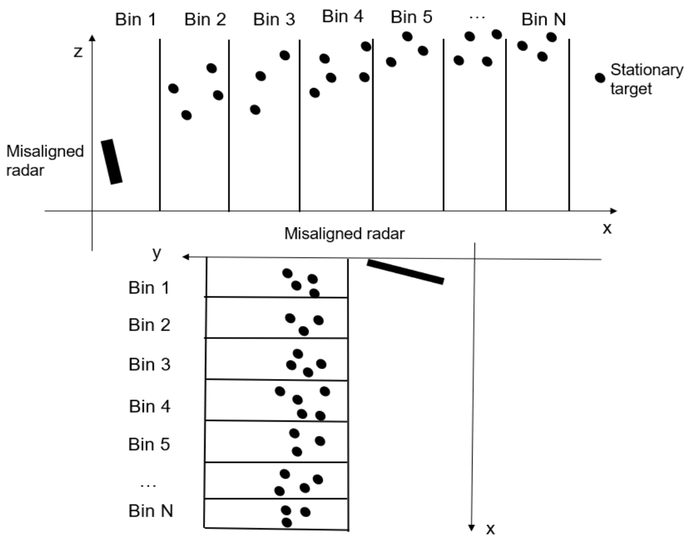

Fig. 3. Example of target association to the longitudinal bin as seen from lateral perspective (upper picture) and birdview perspective (lower picture)

$$i = \left[\frac{\tilde{x} - x_{start}}{x_{step}}\right], \quad x_{start} < \tilde{x} < x_{end}, \quad (3)$$

where i is the height bin to which the target is allocated to, x_{start} and x_{end} are the minimum and maximum longitudinal positions allowed from the target selection phase, while x_{step} represents the granularity of the bins in the longitudinal direction.

Each bin is represented by the number of used targets k and a mean height calculated as in [13] with the filtering factor f, as seen in equation (4):

$$\bar{z}_{i\_current} = \bar{z}_{i\_previous} + f \cdot (\tilde{z} - \bar{z}_{i\_previous}) \quad (4)$$

When a minimum number of height bins (Min_{Bins}) accumulated at least $Min_{targets}$ targets each, a least squares regression process [14] will be applied on the height bins, resulting in a slope m and intercept b, presented in equations (5) and (6):

$$m = \frac{N\sum(i\bar{z}_i) - \sum i \sum \bar{z}_i}{N\sum(i^2) - \sum \bar{z}_i{}^2} \quad (5)$$

$$b = \frac{\sum \bar{z}_i - m \sum i}{N} \quad (6)$$

where N is the number of accepted height bins.

One instance of elevation correction $\Delta\beta$ is calculated as follows:

$$\widetilde{\Delta\beta} = -\tan^{-1}(m) \quad (7)$$

It is necessary to use a filtering approach to produce an accurate estimation. In this paper, we propose to use an exponential moving average with the factor g:

$$\Delta\beta = \Delta\beta_{previous} + g \cdot (\widetilde{\Delta\beta} - \Delta\beta_{previous}) \quad (8)$$

However, a correction $\widetilde{\Delta\beta}$ will only be used in the filtering process if the root mean square error (rmse) from the statistics that led to the correction calculation is small enough. If the process is successful, the new value can be used to correct the raw targets, the bin statistics will be reset, and the process will restart.

III. Purpose-Based Correction

It is essential to have a stable calibration value that can offer long-term electronic compensation for the sensor misalignment during the sensor's lifespan. The algorithm should employ a slower adaptation, in order to produce a steady and accurate calibration value. It is also crucial for the algorithm to quickly converge to the new compensation value in critical scenarios, such as accidents where the bumper is damaged and causes a sensor misalignment. For this, it is recommended to adopt a more rapid and dynamic adaptation, while anticipating a somewhat lower accuracy than the robust filtering method.

We propose computing the robust and dynamic angles using two separate sets of the parameters, in order to achieve the aforementioned objectives, for the following: the longitudinal step for a height bin, the minimum number of required bins, the minimum number of required targets for each bin, the filter factor for angle calculation limit for a successful usage of a calculated correction value. For the robust angle correction $\Delta\beta_r$, we employ a higher number of necessary bins and necessary targets for each bin than the dynamic angle correction mode $\Delta\beta_d$, as well as having a lower exponential moving average factor and high rmse limit.

The correction value $\Delta\beta_u$ that will be used for the target correction and misalignment detection is described in (9):

$$\Delta\beta_u = \begin{cases} \Delta\beta_r, if\ c < h_{min} \\ \Delta\beta_d, if\ c > h_{max} \\ previous\ state\ used, if\ c \in [h_{min}, h_{max}] \end{cases} \quad (9)$$

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

Finally, in order to ensure a low variance for the used correction, after a time Δ_t passes from the moment in which the handover was made from $\Delta\beta_r$ to $\Delta\beta_d$ it means that the dynamic algorithm detected a big enough misalignment in which the robust filtering was not able to converge to yet. In order to provide a stable correction, the robust value will restart from the value of the dynamic correction, while maintaining the robust filtering.

IV. Numerical Results

We give simulation results for the proposed approach in this section. A commercial millimeter wave automotive radar with the following specifications is used to test the algorithm: high resolution in distance, relative velocity, and angle; center frequency of 76.5 GHz; azimuth and elevation angle fields of view of ±90° and ±15°, respectively; and Ethernet communication interface. The conclusions are based on real-world data from several test drives conducted in city, highway, and country road types of streets, under the most favorable climatic and driving circumstances for a rear left radar sensor. This information is utilized as input for our simulation environment.

In the first scenario, we tested the radar sensor mounted on a bike rack, so that the sensor is not affected by the bumper influences and ensures an elevation mounting angle close to 0° using a goniometer. The results are presented in Fig. 4, where the correction values are shown as a function of radar cycles and driven distance, respectively. We can observe a more dynamic behavior from both algorithms until the convergence point is reached, but this behavior is maintained by the dynamic correction method.

The average correction value for both estimate techniques is centered around 0° (0.097° for robust filtering and 0.121° for dynamic filtering).

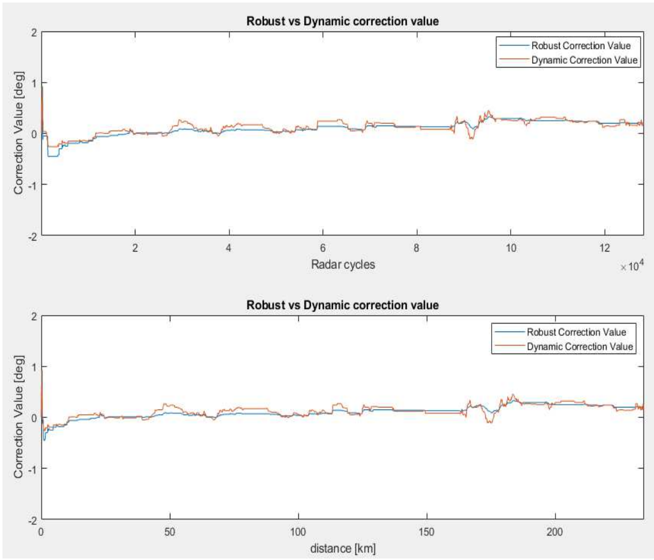

Fig. 4. Vertical correction for 0° scenario. Correction angle over radar cycles (upper picture) and correction angle with respect to the driven distance (lower picture).

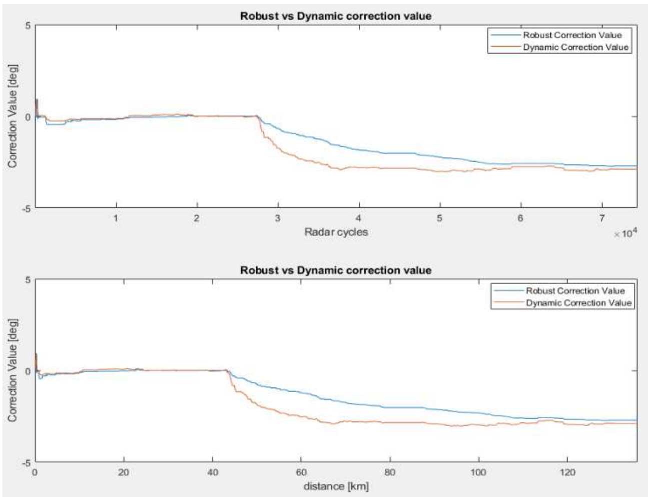

Fig. 5. Vertical correction for 3° error scenario (second scenario). Correction angle over radar cycles (upper picture) and correction angle with respect to the driven distance (lower picture).

In the second misalignment scenario, we introduced an artificial error of 3° after approximately 40 kilometers of driving and tested the convergence of both algorithms. Fig. 5 compares the efficiency of dynamic filtering versus robust filtering, in terms of the time and distance required to converge to the new correction value. The dynamic filtering method reaches the convergence point within 1° accuracy 20 kilometers faster than the robust method (see Fig. 5, lower picture).

In the third scenario, we tested the sensor behind the bumper in a test drive for over 600 kilometers, in different environment conditions, in order to test the stability of the algorithms. This scenario involves driving a vehicle on different types of roads (city, highway) and different weather conditions (snow/no snow). Fig. 6 illustrates the stability of the vertical correction over a long period of time and the statistics can be observed in Table I.

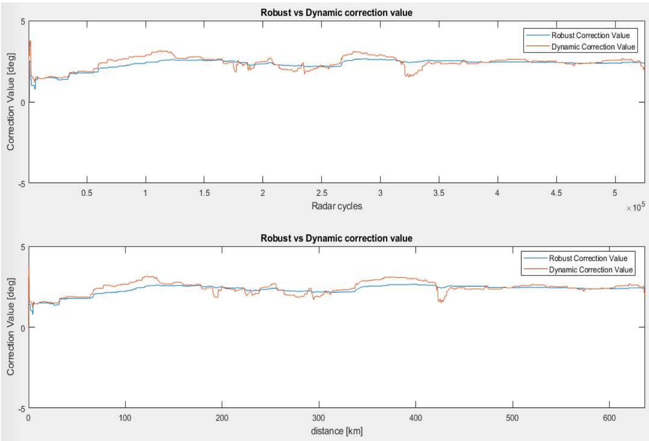

Fig. 6. Vertical correction for a long term evaluation (third scenario). Correction angle over radar cycles (upper picture) and correction angle with respect to the driven distance (lower picture).

TABLE I. COMPARISON OF THE RESULTING CORRECTION VALUES FOR SCENARIO 3

Correction Method	**Mean Value [°]**	**Variance [°]**
Robust filtering $\Delta\alpha_r$	2.323	0.103
Dynamic filtering $\Delta\alpha_d$	2.400	0.159

In the fourth and last scenario, we tested the capabilities of the dynamic algorithm as an initial calibration method to demonstrate the possibility of achieving 0 kilometers performance, with the general purpose of ensuring an accurate starting angle before the vehicle leaves the OEM factory. For this, we executed 7 tests, each consisting in straight driving the car in a local validation area for a few hundred meters.

Fig. 7 and Fig. 8 present the evolution of the vertical correction angle for the tests, both over distance and over the number of successful least squares regression lines generated during each test.

We can observe that most of the tests had concluded in a convergence in less than 100 meters (with the exception of Test Drive Number 5, which finishes in 120 meters) and needed only 30 successfully performed least squares regressions.

Using the values resulted at the end of each test, we obtained a mean vertical alignment angle of 2.071°, a variance of 0.117° and a mean calibration distance of 90 meters.

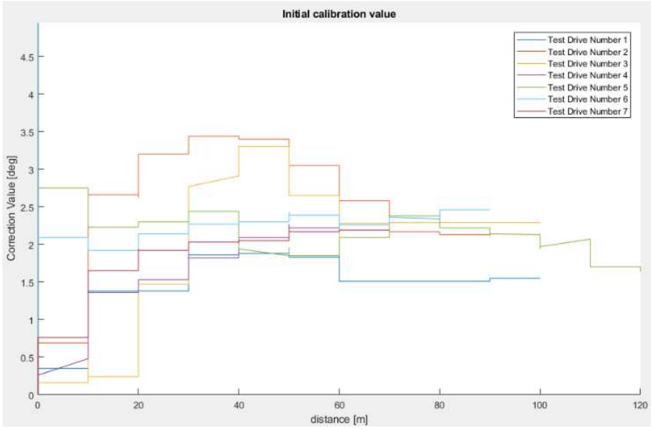

Fig. 7. Initial vertical alignment scenario over distance (scenario 4).

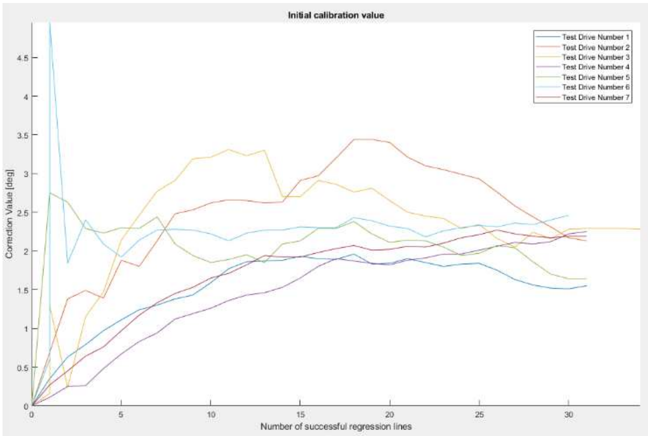

Fig. 8. Initial vertical alignment scenario over the number of successful least squares regressions (scenario 4).

V. CONCLUSIONS

An unsupervised online calibration approach for calculating the vertical misalignment of an automotive radar is proposed in this paper. The method is based on stationary targets and employs two automatic calibration values based on two sets of values for the parameters used, such that one value is stable and accurate in long-term driving scenarios, while the other value provides faster misalignment detection in the event of an accident. Finally, based on hysteresis between the dynamic and robust values, the correction value to be used is decided.

The algorithm was evaluated in a software in the loop (SiL) environment and yielded good results as an initial and continuous calibration. Future work will include the investigation of various regression and filtering approaches, as well as the application of the concept to the calculation of the roll angle of side sensors.

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