Do We Need to Compensate for Motion Distortion and Doppler Effects in Radar-Based Navigation?

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Abstract—In order to tackle the challenge of unfavorable weather conditions such as rain and snow, radar is being revisited as a parallel sensing modality to vision and lidar. Recent works have made tremendous progress in applying radar to odometry and place recognition. However, these works have so far ignored the impact of motion distortion and Doppler effects on radar-based navigation, which may be significant in the self-driving car domain where speeds can be high. In this work, we demonstrate the effect of these distortions on radar-only odometry using the Oxford Radar RobotCar Dataset and metric localization using our own data-taking platform. We present a lightweight estimator that can recover the motion between a pair of radar scans while accounting for both effects. Our conclusion is that both motion distortion and the Doppler effect are significant in different aspects of radar navigation, with the former more prominent than the latter. Code for this project can be found at: https://github.com/keenan-burnett/yeti_radar_odometry.

I. INTRODUCTION

As researchers continue to advance the capabilities of autonomous vehicles, attention has begun to shift towards inclement weather conditions. Currently, most autonomous vehicles rely primarily on cameras and lidar for perception and localization. Although these sensors have been shown to achieve sufficient performance under nominal conditions, rain and snow remain an open problem. Radar sensors, such as the one produced by Navtech [1], may provide a solution.

Due to its longer wavelength, radar is robust to small particles such as dust, fog, rain, or snow, which can negatively impact cameras and lidar sensors. Furthermore, radar sensors tend to have a longer detection range and can penetrate through some materials allowing them to see beyond the line of sight of lidar. These features make radar particularly well-suited for inclement weather. However, radar sensors have coarser spatial resolution than lidar and suffer from a higher noise floor making them challenging to work with.

Recent works have made tremendous progress in applying the Navtech radar to odometry [2]–[7] and place recognition [8]–[10]. However, all of these works make the simplifying assumption that a radar scan is collected at a single instant in time. In reality, the sensor is rotating while the vehicle is moving causing the radar scan to be distorted in a corkscrew fashion. Range measurements of the Navtech radar are also impacted by Doppler frequency shifts resulting from the relative velocity between the sensor and its surroundings. Both distortion effects become more pronounced as the speed of the ego-vehicle increases.

Fig. 1. Our data-taking platform, Boreas, which includes a Velodyne Alpha-Prime (128-beam) lidar, Navtech CIR204-H radar, FLIR Blackfly S monocular camera, and Applanix POSLV GNSS.

Do we need to compensate for motion distortion and Doppler effects in radar-based navigation? In this paper, we demonstrate the effect that motion distortion can have on radar-based navigation. We also provide a lightweight estimator, Motion-Compensated RANSAC, which can recover the motion between a pair of scans and remove the distortion. The Doppler effect was briefly acknowledged in [2] but our work is the first to demonstrate the impact on radar-based navigation and to provide a method for its compensation.

As our primary experiment to demonstrate the effects of motion distortion, we perform radar odometry on the Oxford Radar RobotCar Dataset [11]. As an additional experiment, we perform metric localization using our own data-taking platform, shown in Figure 1. Brief results for object tracking are also provided. Rather than focusing on achieving state-of-the-art navigation results, the goal of this paper is to show that motion distortion and Doppler effects are significant and can be compensated for with relative ease.

The rest of this paper is organized as follows: Sec. II discusses related work, III provides our methodology to match two radar scans while compensating for motion distortion and the Doppler effect, IV has experiments, and V concludes.

II. RELATED WORK

Self-driving vehicles designed to operate in ideal conditions often rely on radar to a role as a secondary sensor as part of an emergency braking system [12]. However, recent advances in Frequency Modulated Continuous Wave (FMCW) radar indicate that it is a promising sensor for navigation and other tasks typically reserved for vision and lidar. Jose and Adams [13] [14] were the first to research...
Data Association

In [3], Cen et al. present their seminal work that has rekindled interest in applying FCMW radar to navigation. Their work presented a new method to extract stable keypoints and perform scan matching using graph matching. Further research in this area has been spurred by the introduction of the Oxford Radar RobotCar Dataset [11], which includes lidar, vision, and radar data from a Navtech radar. Another dataset, which has received less attention, is the MulRan dataset [10], which focuses on comparing place recognition performance between vision, lidar, and radar.

Odometry has recently been a central focus of radar-based navigation research. Components of an odometry pipeline can be repurposed for mapping and localization, which is an ultimate goal of this research. In [3], Cen et al. present an update to their radar odometry pipeline with improved keypoint detection, descriptors, and a new graph matching strategy. Aldera et al. [4] train a focus of attention policy to downsample the measurements given to data association, thus speeding up the odometry pipeline. In [6], Barnes and Posner present a deep-learning-based keypoint detector and descriptor that are learned directly from radar data using differentiable point matching and pose estimation.

Other approaches forego the feature extraction process and instead use the entire radar scan for correlative scan matching. Park et al. [7] use the Fourier Mellin Transform on Cartesian and log-polar radar images to sequentially estimate rotation and translation. In [5], Barnes et al. present a fully differentiable, correlation-based radar odometry approach. In their system, a binary mask is learned such that unwanted distractor features are ignored by the scan matching. This approach currently represents the state of the art for radar odometry performance.

Still others focus on topological localization that can be used by downstream metric mapping and localization systems to identify loop closures. Săftescu et al. [8] learn a metric space embedding for radar scans using a convolutional neural network. Nearest-neighbour matching is then used to recognize locations at test time. Gadd et al. [9] improve this place recognition performance by integrating a rotationally invariant metric space embedding into a sequence-based trajectory matching system previously applied to vision. In [18], Tang et al. focus on localization between a radar on the ground and overhead satellite imagery.

Another recent work using an FMCW radar include the work by Weston et al. [19] that learns to generate occupancy grids from raw radar scans by using lidar data as ground truth. Another is the work by Kaul et al. [20] that trains a semantic segmentation model for radar data using labels derived from lidar- and vision-based semantic segmentation.

Accounting for motion distortion has been treated in the literature through the use of continuous-time trajectory estimation [21]–[25] for lidars [26] and rolling-shutter cameras [27], but these tools are yet to be applied to spinning radar.

Our work focuses on the problem of motion distortion and Doppler effects using the Navtech radar sensor which has not received attention from these prior works. Ideally, our findings will inform future research in this area looking to advance the state of the art in radar-based navigation.

III. METHODOLOGY

Section III-A describes our approach to feature extraction and data association. In Section III-B we present our motion-compensated estimator and a rigid estimator for comparison. Section III-C explains how the Doppler effect impacts radar range measurements and how to compensate for it.

A. Feature Extraction

Feature detection in radar data is more challenging than in lidar or vision due to its higher noise floor and lower spatial resolution. Constant False Alarm Rate (CFAR) [28] is a simple feature detector that is popular for use with radar. CFAR is designed to estimate the local noise floor and capture relative peaks in the radar data. One-dimensional CFAR can be applied to Navtech data by convolving each azimuth with a sliding-window detector.
As discussed in [2], CFAR is not the best detector for radar-based navigation. CFAR produces many redundant keypoints, is difficult to tune, and produces false positives due to the noise artifacts present in radar. Instead, Cen et al. [2] proposed a detector that estimates a signal’s noise statistics and then scales the power at each range by the probability that it is a real detection. In [3], Cen et al. proposed an alternative detector that identifies continuous regions of the scan with high intensity and low gradients. Keypoints are then extracted by locating the middle of each continuous region. We will refer to these detectors as Cen2018 and Cen2019, respectively.

The original formulations of these detectors did not lend themselves to real-time operation. As such, we made several modifications to improve the runtime. For Cen2018, we use a Gaussian filter instead of a binomial filter, and we calculate the mean of each azimuth instead of using a median filter. Where possible, we use multi-threading to parallelize for loops. We do not remove multipath reflections.

Cen2019 was designed to be easier to tune and have less redundant keypoints. However, we found that by adjusting the probability threshold of detections, Cen2018 obtained better odometry performance when combined with our RANSAC-based scan matching. Based on these preliminary tests, we concluded that Cen2018 was the best choice for our experiments. Figure 2(a) shows Cen2018 features plotted on top of a Cartesian radar image.

Raw radar scans output by the Navtech sensor are in polar form. In order to calculate a descriptor for each keypoint, we convert them into Cartesian form. We then calculate an ORB descriptor [29] for each keypoint. There may be better keypoint descriptors for radar data, such as the learned feature descriptors employed in [6]. However, ORB descriptors are quick to implement, rotationally invariant, and resistant to noise. ORB descriptors are sufficient to obtain the initial feature correspondences required by our estimators.

For data association, we perform brute-force matching of ORB descriptors using Hamming distance. We then apply a nearest-neighbor distance ratio test [30] in order to remove false matches. The remaining matches are sent to our RANSAC-based estimators. Figure 2(b) shows the result of the initial data association. Note that there are several outliers. Figure 2(c), (d) shows the remaining inliers after performing RANSAC.

B. Motion Distortion

The output of data association is not perfect and often contains outliers. As a result, it is common to employ an additional outlier rejection scheme during estimation. In this paper, we use RANSAC [31] to find an outlier-free set that can then be used to estimate the desired transform. If we assume that two radar scans are taken at times $t_1$ and $t_2$, then the transformation between them can be estimated directly using the approach described in [32].

During each iteration of RANSAC, a random subset of size $S$ is drawn from the initial matches and a candidate transform is generated. If the number of inliers exceeds a desired threshold or a maximum number of iterations is reached, the algorithm terminates. Radar scans are 2D and as such we use $S = 2$. The estimation process is repeated on the largest inlier set to obtain a more accurate transform. We will refer to this approach, which ignores motion distortion, as rigid RANSAC.

Our derivation of motion-compensated RANSAC follows closely from [21]. However, we are applying the algorithm to a scanning radar in 2D instead of a two-axis scanning lidar in 3D. Furthermore, our derivation is shorter and uses updated notation from [33].

The principal idea behind motion-compensated RANSAC is to estimate the velocity of the sensor instead of estimating a transformation. We make the simplifying assumption that the linear and angular velocity between a pair of scans is constant. The combined velocity vector $\varpi$ is defined as

$$\varpi = \begin{bmatrix} \nu \\ \omega \end{bmatrix},$$

where $\nu$ and $\omega$ are the linear and angular velocity in the sensor frame. To account for motion distortion, we remove the assumption that radar scans are taken at a single instant in time. Data association produces two sets of corresponding measurements, $y_{m,1}$ and $y_{m,2}$, where $m = 1...M$. Each pair of features, $m$, is extracted from sequential radar frames 1 and 2 at times $t_{m,1}$ and $t_{m,2}$. The temporal difference between a pair of measurements is $\Delta t_m := t_{m,2} - t_{m,1}$. The generative model for measurements is given as

$$y_{m,1} := f(T_s(t_{m,1}) \mathbf{p}_m) + \mathbf{n}_{m,1},$$
$$y_{m,2} := f(T_s(t_{m,2}) \mathbf{p}_m) + \mathbf{n}_{m,2},$$

where $f(\cdot)$ is a nonlinear transformation from Cartesian to cylindrical coordinates and $T_s(t)$ is a 4 x 4 homogeneous transformation matrix representing the pose of the sensor frame $F_s$ with respect to the inertial frame $F_i$ at time $t$. $\mathbf{p}_m$ is the original landmark location in the inertial frame. We assume that each measurement is corrupted by zero-mean Gaussian noise: $\mathbf{n}_{m,1} \sim \mathcal{N}(0, R_{m,1})$. The transformation between a pair of measurements is defined as

$$T_m := T_s(t_{m,2}) T_s(t_{m,1})^{-1}.$$ (3)

To obtain our objective function, we convert feature locations from polar coordinates into local Cartesian coordinates:

$$\mathbf{p}_{m,2} = f^{-1}(y_{m,2}),$$
$$\mathbf{p}_{m,1} = f^{-1}(y_{m,1}).$$

We then use the local transformation $T_m$ to create a pseudomeasurement $\mathbf{p}_{m,2}$:

$$\mathbf{p}_{m,2} = T_m \mathbf{p}_{m,1}.$$ (6)

The error is then defined in the sensor coordinates and summed over each pair of measurements to obtain our objective function:

$$e_m = \mathbf{p}_{m,2} - \mathbf{p}_{m,2},$$
$$J(\varpi) := \frac{1}{2} \sum_{m=1}^{M} e_m^r R_{cart,m}^{-1} e_m.$$ (8)
Here we introduce some notation for dealing with transformation matrices in \( SE(3) \). A transformation \( \mathbf{T} \in SE(3) \) is related to its associated Lie algebra \( \xi^\oplus \in \mathfrak{se}(3) \) through the exponential map:

\[
\mathbf{T} = \begin{bmatrix} \mathbf{C} & \mathbf{r} \\ 0^T & 1 \end{bmatrix} = \exp(\xi^\oplus),
\]

where \( \mathbf{C} \) is a \( 3 \times 3 \) rotation matrix, \( \mathbf{r} \) is a \( 3 \times 1 \) translation vector, and \( (\cdot)^\oplus \) is an overloaded operator that converts a vector of rotation angles \( \phi \) into a member of \( \mathfrak{so}(3) \) and \( \xi \) into a member of \( \mathfrak{se}(3) \):

\[
\phi^\oplus = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \phi_3 \end{bmatrix}^\oplus := \begin{bmatrix} 0 & -\phi_3 & \phi_2 \\ \phi_3 & 0 & -\phi_1 \\ -\phi_2 & \phi_1 & 0 \end{bmatrix},
\]

\[
\xi^\oplus = \begin{bmatrix} \rho \\ \phi \end{bmatrix}^\oplus := \begin{bmatrix} \rho^\oplus \\ \phi^\oplus \end{bmatrix}.
\]

Given our constant-velocity assumption, we can convert from a velocity vector \( \varpi \) into a transformation matrix using the following formula:

\[
\mathbf{T} = \exp(\Delta t \varpi^\oplus).
\]

In order to optimize our objective function \( J(\varpi) \), we first need to derive the relationship between \( \mathbf{T}_m \) and \( \varpi \). The velocity vector \( \varpi \) can be written as the sum of a nominal velocity \( \varpi \) and a small perturbation \( \delta \varpi \). This lets us rewrite the transformation \( \mathbf{T}_m \) as the product of a nominal transformation \( \mathbf{T}_m \) and a small perturbation \( \delta \mathbf{T}_m \):

\[
\mathbf{T}_m = \exp(\Delta t_m (\varpi + \delta \varpi)^\oplus) = \delta \mathbf{T}_m \mathbf{T}_m.
\]

Let \( g_m(\varpi) := \mathbf{T}_m \mathbf{p}_{m,1} \), which is nonlinear due to the transformation. Our goal is to linearize \( g_m(\varpi) \) about a nominal operating point. We can rewrite \( g_m(\varpi) \) as:

\[
g_m(\varpi) = \exp(\Delta t_m \delta \varpi^\oplus) \mathbf{T}_m \mathbf{p}_{m,1},
\]

\[
\approx (1 + \Delta t_m \delta \varpi^\oplus) \mathbf{T}_m \mathbf{p}_{m,1},
\]

where we use an approximation for small pose changes. We swap the order of operations using the \( (\cdot)\odot \) operator [33]:

\[
g_m(\varpi) = \mathbf{T}_m \mathbf{p}_{m,1} + \Delta t_m (\mathbf{T}_m \mathbf{p}_{m,1}) \odot \delta \varpi
\approx \mathbf{g}_m + \mathbf{G}_m \delta \varpi,
\]

\[
\mathbf{p} \odot = \begin{bmatrix} \rho \\ \eta \end{bmatrix} \odot = \begin{bmatrix} \eta \mathbf{1} \\ \mathbf{0}^T \\ -\rho^\oplus \end{bmatrix}.
\]

We can now rewrite the error function from (7):

\[
\mathbf{e}_m \approx \mathbf{p}_m - \mathbf{g}_m - \mathbf{G}_m \delta \varpi
\approx \bar{\mathbf{e}}_m - \mathbf{G}_m \delta \varpi.
\]

By inserting this equation for the error function into the objective function from [9], and taking the derivative with respect to the perturbation and setting it to zero, \( \frac{\partial J(\varpi)}{\partial \delta \varpi} = 0 \), we obtain the optimal update:

\[
\delta \varpi^* = \left( \sum_m \mathbf{G}_m^T \mathbf{R}_{cart,m}^{-1} \mathbf{G}_m \right)^{-1} \left( \sum_m \mathbf{G}_m^T \mathbf{R}_{cart,m}^{-1} \bar{\mathbf{e}}_m \right),
\]

where \( \mathbf{R}_{cart,m} = \mathbf{H}_m \mathbf{R}_{m,2} \mathbf{H}_m^T \) is the covariance in the local Cartesian frame, \( \mathbf{h}(\cdot) = \mathbf{f}^{-1}(\cdot) \), and \( \mathbf{H}_m = \frac{\partial \mathbf{h}}{\partial \mathbf{f}} \). The optimal perturbation \( \delta \varpi^* \) is used in a Gauss-Newton optimization scheme and the process repeats until \( \varpi \) converges.

This method allows us to estimate the linear and angular velocity between a pair of radar scans directly while accounting for motion distortion. These velocity estimates can then be used to remove the motion distortion from a measurement relative to a reference time using (12). MC-RANSAC is intended to be a lightweight method for showcasing the effects of motion distortion. A significant improvement to this pipeline would be to use the inliers of MC-RANSAC as an input to another estimator, such as [24]. The inliers could also be used for mapping and localization or SLAM.

### C. Doppler Correction

In order to compensate for Doppler effects, we need to know the linear velocity of the sensor \( v \). This can either be obtained from a GPS/IMU or using one of the estimators described above. As shown in Figure [3] the motion of the sensor results in an apparent relative velocity between the sensor and its surrounding environment. This relative velocity causes the received frequency to be altered according to the Doppler effect. Note that only the radial component of the velocity \( u = v \cos(\phi) \) will result in a Doppler shift. The Radar Handbook by Skolnik [34] provides an expression for the Doppler frequency:

\[
f_d = \frac{2v \cos(\phi)}{\lambda},
\]

where \( \lambda \) is the wavelength of the signal. Note that for an object moving towards the radar \( (u > 0) \) or vice versa, the Doppler frequency will be positive resulting in a higher
received frequency. For FMCW radar such as the Navtech sensor, the distance to a target is determined by measuring the change in frequency between the received signal and the carrier wave \( \Delta f \):

\[
r = \frac{c \Delta f}{2(\text{df}/\text{dt})},
\]

(20)

where \( \text{df}/\text{dt} \) is the slope of the modulation pattern used by the carrier wave and \( c \) is the speed of light. FMCW radar requires two measurements to disentangle the frequency shift resulting from range and relative velocity. Since the Navtech sensor scans each azimuth only once, the measured frequency shift is the combination of both the range difference and Doppler frequency. From Figure 4, we can see that a positive Doppler frequency \( f_d \) will result in an increase in the received frequency and in turn a reduction in the observed frequency difference \( \Delta f \). Thus, a positive Doppler frequency will decrease the apparent range of a target.

The Navtech radar operates between 76 GHz and 77 GHz resulting in a bandwidth of 1 GHz. Navtech states that they use a sawtooth modulation pattern. Given 1600 measurements per second and assuming the entire bandwidth is used for each measurement, \( \text{df}/\text{dt} \approx 1.6 \times 10^{12} \).

Hence, if the forward velocity of the sensor is 1 m/s, a target positioned along the horizontal axis (forward) of the sensor would experience a Doppler frequency shift of 510 Hz using (19). This increase in the frequency of the received signal would decrease the apparent range to the target by 4.8 cm using (20). Naturally, this effect becomes more pronounced as the velocity increases.

Let \( \beta = f_t/(\text{df}/\text{dt}) \) where \( f_t \) is the transmission frequency \( (f_t \approx 76.5 \text{ GHz}) \). In order to correct for the Doppler distortion, the range of each target needs to be corrected by the following factor:

\[
\Delta r_{\text{corr}} = \beta v \cos(\phi).
\]

(21)

We use this simple correction in all our experiments with the velocity \( v \) coming from our motion estimator.

### IV. EXPERIMENTAL RESULTS

In order to answer the question posed by this paper, we have devised two experiments. The first is to compare the performance of rigid RANSAC and MC-RANSAC (with or without Doppler corrections) for the task of radar odometry on the Oxford Radar RobotCar Dataset [11]. The second compares the performance of these two estimators when compensating for motion distortion has a modest impact on radar odometry. We use KITTI-style odometry metrics [35] to quantify the translational and rotational drift as is done in [6]. The metrics are obtained by averaging the translational and rotational drifts for all subsequences of lengths (100, 200, ..., 800) meters. The table shows that motion-compensated RANSAC results in a 21.9% reduction in translational drift and a 15.6% reduction in rotational drift. This shows that compensating for motion distortion has a modest impact on radar odometry. The table also indicates that Doppler effects have a negligible impact on odometry.

### A. Odometry

Our goal is to make a fair comparison between two estimators where the main difference is the compensation of distortion effects. To do this, we use the same number of maximum iterations (100), and the same inlier threshold (0.35 m) for both rigid RANSAC and MC-RANSAC. We also fix the random seed before running either estimator to ensure that the differences in performance are not due to the random selection of subsets.

Odometry results are obtained by compounding the frame-to-frame scan matching results for each sequence. Note that we do not use a motion prior or perform any additional smoothing on the odometry. Three sequences were used for parameter tuning. The remaining 29 sequences are used to provide test results.

Table 1 summarizes the results of the odometry experiment. We use KITTI-style odometry metrics [35] to quantify the translational and rotational drift as is done in [6].

| Method                  | Translational Error (%) | Rotational Error (deg/m) |
|-------------------------|-------------------------|--------------------------|
| Rigid RANSAC            | 4.4935                  | 0.0141                   |
| MC-RANSAC              | 3.5080                  | 0.0119                   |
| MC-RANSAC + Doppler    | 3.5012                  | 0.0118                   |

### TABLE I

**RADAR ODOMETRY RESULTS.** Odometry results from [6].

It should be noted that a large fraction of the Oxford dataset was collected at low speeds (0-5 m/s). This causes the motion distortion and Doppler effects to be less noticeable than they would be otherwise.
B. Localization

The purpose of this experiment is to demonstrate the impact of motion distortion and Doppler effects on metric localization. As opposed to the previous experiment, we localize between scans taken while driving in opposite directions. While the majority of the Oxford Radar dataset was captured at low speeds (0-10 m/s), in this experiment we only use radar frames where the ego-vehicle’s speed was above 10 m/s. For this experiment, we use our own data-taking platform, shown in Figure 1, which includes a Velodyne Alpha-Prime lidar, Navtech CIR204-H radar, Blackfly S camera, and an Applanix POSLV GNSS.

Ground truth for this experiment was obtained from a 10 km drive using post-processed GNSS data provided by Applanix, which has an accuracy of 12 cm in this case. Radar scans were initially matched by identifying pairs of proximal scans on the outgoing and return trips based on GPS data. The Navtech timestamps were synchronized to GPS time to obtain an accurate position estimate.

Our first observation was that localizing against a drive in reverse is harder than odometry. When viewed from different angles, objects have different radar cross sections, which causes them to appear differently. As a consequence, radar scans may lose or gain features when pointed in the opposite direction. This change in the radar scan’s appearance was sufficient to prevent ORB features from matching.

As a replacement for ORB descriptors, we turned to the Radial Statistics Descriptor (RSD) described in [2], [3]. Instead of calculating descriptors based on the Cartesian radar image, RSD operates on a binary Cartesian grid derived from the detected feature locations. This grid can be thought of as a radar target occupancy grid. For each keypoint, RSD divides the binary grid into M azimuth slices and N range bins centered around the keypoint. The number of keypoints (pixels) in each azimuth slice and range bin is counted to create two histograms. In [3], a fast Fourier transform of the azimuth histogram is concatenated with a normalized range histogram to form the final descriptor.

In our experiment, we found that the range histogram was sufficient on its own, with the azimuth histogram offering only a minor improvement. It should be noted that these descriptors are more expensive to compute (60 ms) and match (30 ms) than ORB descriptors.

The results of our localization experiment are summarized in Table II. In each case, we are using our RANSAC estimator from Section III. The results in the table are obtained by calculating the median translation and rotation error. Compensating for motion distortion results in a 21.6% reduction in translation error. Compensating for Doppler effects results in a further 9.3% reduction in translation error. Together, compensating for both effects results in a 29.0% reduction in translation error. Note that the scan-to-scan translation error is much larger than in the odometry experiment due to the increased difficulty of localizing against a reverse drive. Figure 6 depicts a histogram of the localization errors in this experiment.

Fig. 6. This figure highlights the impact that motion distortion can have on the accuracy of radar-based odometry. Note that motion-compensated RANSAC (MC-RANSAC) is much closer to the ground truth.

| Method                        | Trans. Error (m) | Rot. Error (deg) |
|-------------------------------|------------------|------------------|
| No Compensation               | 3.4262           | 0.6228           |
| Motion-Compensated            | 2.6850           | 0.9952           |
| Motion-Compensated + Doppler-Compensated | 2.4342 | 0.7248           |
C. Object Tracking

In this section we present anecdotal evidence of the impact of motion distortion and Doppler effects on object tracking using the Navtech radar. In Figure 8, we have plotted points from our Velodyne lidar in red on top of a Cartesian radar image. In this example, the ego-vehicle is driving at a moderate speed of 16 m/s with vehicles approaching from the opposite direction on the left-hand side of the road. Since lidar measurements are not affected by Doppler distortion and are less affected by motion distortion due their higher spin rate, they can be used to visualize the amount of distortion present in the radar scan. The lidar and radar scans have been aligned spatially and temporally using GNSS data. Figure 8(a) shows what the original alignment looks like when distorted. Figure 8(b) shows what the alignment looks like after compensating for motion distortion and Doppler effects. Note that the static objects such as the trees on both sides of the road align much better with the lidar data after the distortion effects are removed. Also note the high amount of residual Doppler distortion present in the oncoming vehicles, boxed in orange; here we do not know the other vehicles’ velocities and therefore the true relative velocity with respect to the ego-vehicle.

V. CONCLUSION

For the problem of odometry, compensating for motion distortion had a noticeable impact of reducing translational drift by 21.9%. Compensating for Doppler effects had a negligible effect on odometry performance. We postulate that Doppler effects are negligible for odometry because their effects are quite similar from one frame to the next. In our localization experiment, we observed that compensating for motion distortion and Doppler effects reduced translation error by 21.6% and 9.3% respectively with a combined reduction of 29.0%. We also provided anecdotal evidence that the Doppler effect becomes important for object tracking with high relative velocities. In summary, the Doppler effect can likely be safely ignored for the radar odometry problem but motion distortion should be accounted for to achieve the best results. For metric localization, especially for localizing in the opposite direction from which the map was built, both motion distortion and Doppler effects should be compensated. Accounting for these effects is computationally cheap, but requires an accurate estimate of the linear and angular velocity of the sensor.

For future work, we will investigate applying more powerful estimators such as [24] to odometry and the full mapping and localization problem. We will also investigate learned features and the impact of seasonal changes on radar maps.
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