A Framework for Active Learning of Beam Alignment in Vehicular Millimeter Wave Communications by Onboard Sensors

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Abstract: Estimating time-selective millimeter wave wireless channels and then deriving the optimum beam alignment for directional antennas is a challenging task. To solve this problem, one can focus on tracking the strongest multipath components (MPCs). Aligning antenna beams with the tracked MPCs increases the channel coherence time by several orders of magnitude. This contribution suggests tracking the MPCs geometrically. The derived geometric tracker is based on algorithms known as Doppler bearing tracking. A recent work on geometric-polar tracking is reformulated into an efficient recursive version. If the relative position of the MPCs is known, all other sensors on board a vehicle, e.g., lidar, radar, and camera, will perform active learning based on their own observed data. By learning the relationship between sensor data and MPCs, onboard sensors can participate in channel tracking. Joint tracking of many integrated sensors will increase the reliability of MPC tracking.

Keywords: adaptive filters; autonomous vehicles; directive antennas; doppler measurement; intelligent vehicles; machine learning; millimeter wave communication

1 Introduction

Millimeter wave (mmWave) frequency bands have been a candidate for vehicular communication for several decades [1]–[3]. MmWave train-to-infrastructure path loss was measured in [2], while the transmission behaviour of mmWave for communication between vehicles was examined in [1]. Recent advances in mmWave circuit technology have aroused interest in mmWave vehicular communication [3] and in joint vehicular communication and radar [4]. MmWaves offer large bandwidths and enable raw data exchange between vehicles [5]. The main problems with vehicular mmWave communication are the direct proportionality of the maximum Doppler shift and the carrier frequency as well as the beam alignment challenge in the dynamic environment. In [6] and [7], however, it has been shown theoretically that directional antennas intended for mmWaves function as spatial filters. The Doppler effect and thus the time selectivity is drastically reduced by beamforming. This is shown experimentally in [8] and [9]. There seems to be a consensus that channel tracking tackles the second challenge of the dynamic environment [10]–[21]. Channel tracking is the process of causally estimating the current or future direction of the line-of-sight (LOS) component or other strong multipath components (MPCs) based on previous measurements. The main advantage of channel tracking is the extended coherence time after successful beamforming. The channel coherence time of the beam aligned channel is several orders of magnitude longer than that for omnidirectional reception [7]. A subsequent channel estimation therefore runs on a coarser time grid.

The work in [10] adopts the idea and formalism of [21] and applies them directly to THz lens antennas. Extended Kalman filters are used in [11], [18], and [19] to track the beam directions based on channel gain measurements. In [15], domain

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knowledge is used and it is argued that the road implicitly determines the direction in which a vehicle is expected. Beam training is avoided by using this geometric prior knowledge. Assuming a constant angular acceleration that is motion along circles, [20] proposes an algorithm based on the unscented Kalman filter. Probabilistic beam tracking is suggested in [16]. Moreover, in [13] and [14] the stochastic Newton method is used, and these algorithms surpass IEEE 802.11ad based approaches and compressive sensing based approaches [17]; the work in [13] and [14], shows good performance for angular velocities of up to $5^\circ$/s.

In [22], it was first proposed to utilize the Doppler information for mmWave beam tracking. Measurements in [23] clearly demonstrate that interacting objects, such as overtaking cars, produce distinguishable MPCs in the Doppler profile. The proposed algorithm herein, exploiting Doppler information, is assessed in scenarios where the angular velocity exceeds 100$^\circ$/s for a short duration.

This contribution proposes to track the MPCs geometrically given quantized angular (azimuth) measurements and noisy Doppler observations. The quantized angular information is obtained by an analog or hybrid beamforming array or a dielectric lens [24]. "Geometric" refers to the $(x,y)$ coordinates originating in the antenna array and the relative velocity $(\dot{x},\dot{y})$ to the receiver motion. We assume that the transmitter, the receiver, and the interacting objects move without acceleration. Under these assumptions, algorithms performing target-motion analysis by means of Doppler-bearing measurements [25]–[27] are directly applicable. The work in [25]–[27] proposes a formulation called "pseudolinear." Pseudolinear refers to a formulation where the nonlinearities are either hidden in a measurement (regression) matrix or are lumped within the noise term. This leads to the undesirable consequence of noise correlation of the measurements and the measurement matrix, eventually leading to biased solutions [26]. An early work [25] removes this bias by the method of instrumental variables. Due to a potential divergence of the instrumental variables approach [27], later work [26], [27] employs the method of total least squares. To apply total least squares, error covariance matrices must be known. The proposed approach is inspired by [27], but does not need knowledge about the error covariances.

In addition to the excellent angular tracking performance of the proposed algorithm, the obtained geometric information of the MPCs can be utilized to learn the MPCs from other sensors on board of automated vehicles [5]. The concept of using external information for improved channel estimation was recently reintroduced, see [29] and [30] and the reference therein. Machine learning for configuring wireless links has also been proposed in the context of WLAN and mobile communications [31]–[33]. The actual machine learning implementation is not within the scope of this contribution. This contribution focuses on a framework for active learning of beam alignment. This paper is an extended version of [34].
challenge and more and more tasks are already shifted towards fog and cloud computing units [45], [46]. To use these gigabytes of data for the tracking of MPCs, every tracked object of the onboard sensors must be labelled as "MPC" or "no MPC" (pedestrian, non-communicating car, static objects, etc.). This leads to high labelling efforts and to a huge amount of training data where most of labels will be "no MPC".

The key idea is now to exploit the geometric position of the MPC and thus to only label those targets that are in the vicinity of the MPC. The process of associating MPCs to "targets" is illustrated with black circles in Fig. 1. Instead of human (or any other oracle) labelling there is an active choice of the system which targets to consider for learning the beam alignment. After a successful learning phase, all sensors on board should later do the channel tracking. By using machine learning, one can eliminate or significantly reduce the beam measurements needed for the currently proposed tracking algorithm. If for all of these target states it is known whether they belong to the LOS component or to a specular reflection, the onboard sensors will track the MPCs.

In this sense this paper provides an algorithm which determines the geometric positions of the communication partners in order to label them as interesting training samples.

3 Measurement, Regression, and Projection Model

The regression model is based on the model proposed in [27]. The main idea of [27] is to track non-accelerating objects on linear trajectories in polar coordinates; target motion analysis in polar coordinates yields a smaller bias than in rectangular coordinates. The regression model is hence formulated in polar coordinates. This idea is illustrated in Fig. 2. The original tracking problem of [27] uses a running reference (blue). Thereby at each time the current state is estimated. This approach produces an increasing system of equations, anew, at any time. In contrast to [27], the proposed algorithm will use a fixed reference (red) and gather only one new equation per time step. Thereby the estimate of the initial state is refined and its accuracy is improved over time, as in [25]. Through this reformulation, the initial state-vector is estimated recursively. The state vector at current and future times is predicted by a projection.

3.1 Quantized Angular Measurements by the UCA Codebook

For target motion analysis a noisy bearing (angular) observation is assumed where the noise is usually modelled Gaussian [27]. In this study, however, quantized angular observations will occur. A 60 GHz uniform circular array (UCA) with \( N = 64 \) elements equidistantly spaced on a radius of \( r_{\text{UCA}} = N/2 \cdot \lambda/2 \approx 8 \) cm is used. The half power beam width is \( \theta_{\text{BWP}} \approx 2 \pi/N \approx 6^\circ \). The UCA is inherently symmetric in its azimuthal resolution. In contrast to uniform planar arrays, the UCA beam pattern does not change with the pointing direction. To save cost, analog precoding (beamforming) with 4 bit RF phase-shifters is employed. The phase shifts are pre-computed in a codebook spaced by \( \theta_{\text{BWP}}/2 \) which gives \( 2\pi/[2\pi/(N/2)] \) \( = 2 \cdot N = 128 \) codebook entries. Beampattern of the UCA is shown in Fig. 3.

3.2 Regression Model

The angle spanning from initial azimuth \( \phi_i \) to the current
azimuth $\phi_i$ is denoted by $b_{ik}$. In Fig. 2, w.l.o.g. $i$ is set to zero. The range (at time $k$) is denoted by $r_i$. The time intervals are denoted by $t_{ik}$. The Doppler relevant angle at time $k$, that is $\alpha_i$, is measured from the velocity vector $v$ to the radial speed component. The basis equation is the sine law evaluated to the radial, that is $\nu_i$, w.l.o.g. $2$. In Fig. 3 is set to zero oppositely symmetric for all directions; illustrated by the red pattern pointing in opposite direction.

$\frac{r_i}{\sin(\alpha_i)} = \frac{r_{ik}}{\sin(b_{ik})} \tag{1}$

Now Equ. (1) is reformulated into a so-called pseudo-linear formulation [28]:

$\sin(b_{ik}) - t_{ik} \cos(b_{ik}) t_{ik} \sin(b_{ik}) v \sin(\alpha_i) = 0, \tag{2}$

where all nonlinearities are regressors now. For each observation-time $k$, one equation in the form of Equ. (2) is obtained. This is written compactly in matrix-vector notation:

$A_{b_{ik}} x = 0. \tag{3}$

The solution to Equ. (3) is not unique. Next Doppler-shift observations $r_{ik}$ are exploited. These are calculated by

$\nu_i = \frac{v}{\lambda} \cos(\alpha_i) = \frac{v}{\lambda} \cos(\alpha_i - b_{ik}). \tag{4}$

Equ. (4) is re-written into the same form as Equ. (2):

$0, \sin(b_{ik}) - t_{ik} \cos(b_{ik}) v \sin(\alpha_i) = 0. \tag{5}$

This leads again to a system of equations in form of

$A_{b_{ik}} x = \nu_{ik}. \tag{6}$

One finally arrives at the augmented system of equations:

$\begin{bmatrix} A_{b_{ik}} & x \end{bmatrix} = \begin{bmatrix} 0 & \nu_{ik} \end{bmatrix}. \tag{7}$

This system of equations has a unique solution and is called “Doppler-bearing tracking” in the literature [25]–[27]. In this contribution, Equ. (7) is solved via the method of least squares (LS). Note that Equ. (7) is equivalent to

$\begin{bmatrix} A_{b_{ik}}(k-1) & 0 \end{bmatrix} \begin{bmatrix} A_{b_{ik}}(k-1) & \nu_{ik} \end{bmatrix} = \begin{bmatrix} \nu_{ik} \end{bmatrix}. \tag{8}$

In Equ. (8), the previous observations are separated from the current one. This structure allows for a recursive least squares (RLS) implementation. The recursive estimate of $\nu_i$ at time $k$ will be denoted by $\hat{x}_{ik}$, in the sequel.

The angular separations $b_{ik}$ in Equs. (1)–(8) are not known and must be estimated. The variable $b_{ik}$ has to be replaced by $\hat{b}_{ik}$, the estimated quantity, in the equations above. Such measurement equations are called “errors-in-variables model” in the statistics literature [47]. The estimation of $\hat{b}_{ik}$ is initially done by training sequences. For each time $k$, the current azimuth angle $\phi_i$ is estimated by aid of beam sweeping, that is, the codebook scan. All possible beams are iterated and the codebook entry (azimuth direction) with largest receive power is selected. Next we obtain $\hat{b}_{ik} = \phi_i - \hat{\phi}_i$. Later on, onboard sensors might provide the estimate of $\phi_i$ and codebook scans can be avoided or at least performed less frequently.

With the estimate of the initial state-vector $\hat{x}_{ik}$, we calculate the initial $(x,y)$ position and the velocity vector $(\dot{x}, \dot{y})$ based on the polar representation. The range $\hat{r}_i$ is the first element of the initial state-vector estimate, that is $\hat{x}_{ik}(1)$. The azimuth angle $\hat{\phi}_i$ is estimated through designated pilots. The velocity $\dot{v}_i$ is calculated through the initial state-vector estimate and the angle of the velocity vector to the $x$-axis $\varphi$ is calculated through the initial state-vector estimate as well:

$\dot{v}_i = \sqrt{(\hat{v}_{ik}(2))^{2} + (\hat{v}_{ik}(3))^{2}}, \tag{9}$

$\varphi = \hat{\alpha} + \hat{\phi}_i = \arctan(\hat{x}_{ik}(2), \hat{x}_{ik}(3)) + \hat{\phi}_i$.

### 3.3 Projection Model

A suitable projection from the initial state vector to arbitrary time points was recently derived from [48]. The assumption of a linear trajectory with non-accelerating MPCs leads to a static velocity vector. Only the range $\hat{r}_i$ and the azimuth angle $\hat{\phi}_i$ need to be projected to current (or future) time points $k$. The range projection $\hat{r}_i$ is calculated through [48]:

\begin{align*}
A_{b_{ik}}(k) & x = \nu_{ik} \\
A_{b_{ik}}(k) & x = \nu_{ik}.
\end{align*}
set between cars becomes very small. To increase robustness against quantization effects of the codebook and against the geometry dependent structure of \( A_k \), an \( \mathcal{H}_\infty \) filter with a finite time horizon \([49, 50]\) is applied. The objective of an \( \mathcal{H}_\infty \) filter is to keep the error relation below bounded:

\[
\sup_{\hat{x}_k, x_k, u_k} \left\| \hat{x}_k - x_k \right\|^2 + \sum_{i=1}^n \left( \left\| u_k \right\|^2 + \sum_{i=1}^n \left\| n_i \right\|^2 \right) < \gamma^2.
\]

The vector \( \hat{x}_0 \) denotes the initial guess of the state vector (in the simulations \( \hat{x}_0 = 0 \), \( u_k = 0 \), and \( \gamma = 2 \)). The \( \mathcal{H}_\infty \) filter has a higher error floor and a higher complexity than the plain RLS solution. As a quantized codebook is used, subsequent measurements potentially provide equal azimuth angle measurements. Due to the structure of \( a_{u,k} \) and \( a_{n,k} \), the regression matrix is likely to be rank-deficient, initially. Therefore, the algorithm starts with the \( \mathcal{H}_\infty \) filter and switches to the RLS filter after three different azimuth angles are measured. The recursive solution to Eqn. (8) is given as

\[
\hat{x}_{i,k} = \hat{x}_{i,k-1} + P_{i,k-1} A_k^T H_{i,k} (y_k - A_k \hat{x}_{i,k-1}),
\]

where

\[
H_{i,k} = \begin{cases} I, & \text{for RLS} \\ (I + A_k P_k A_k^T)^{-1}, & \text{for \( \mathcal{H}_\infty \)} \end{cases}
\]

The covariance matrix \( P_{i,k} \) fulfills the recursion (17). By aid of the Woodbury matrix identity, the inverse of the covariance matrix reveals a remarkably simple structure, see Eqn. (19). If \( P_{i,k}^{-1}(\gamma) \) is a positive-definite matrix, the possible worst case energy (14) is bounded by \( \gamma^2 \) [50]. Updating \( P_{i,k}^{-1} \) and performing an inverse of a symmetric, positive-definite matrix of size 3×3 is more efficient than updating \( P_{i,k} \) directly:

\[
P_{i,k}^{-1} = \begin{cases} P_{i,k-1}^{-1} - P_{i,k-1}^{-1} A_k^T (I + A_k P_{i,k-1} A_k^T)^{-1} A_k P_{i,k-1}^{-1}, & \text{for RLS} \\ P_{i,k}^{-1} - P_{i,k}^{-1} A_k^T A_k R_{i,k}^{-1} [A_k^T A_k - P_{i,k}^{-1}], & \text{for \( \mathcal{H}_\infty \)} \end{cases}
\]

The performance bounds-Genie Estimators

Due to quantized angular observations, the already derived Cramér-Rao bound [25] is not applicable. We will compare the obtained estimation results to two other bounds; firstly, to the “error-free regressors model.” Here, the azimuth angles \( \hat{\Phi}_i \) are assumed to be perfectly known, hence unquantized, and
the proposed sequential estimator for the first Monte Carlo run.
the respective scatter plots of the estimated position of
date rate) and 50 ms update rate (Fig. 20 are plotted in
proposed sequential implementation from Section 4
The normalized mean squared error of the prior work \[\text{Equ. (3)}\], the
within the sketch of the manoeuvre as bl
a
ms update rate or five codebook entries for
algorithm only probes the closest three codebook entries for
20 ms update rate or five codebook entries for 50 ms update rate.
This gives a speed up of a factor 128/3 \(\approx 43\) or 128/5 \(\approx 26\) as
called an encounter in the Doppler shift equa

### 6 Simulations

The simulations focus on line-of-sight scenarios. Note that
the measured Doppler measurements \(\nu\), the LS solution (21) is the maximum likel
hood estimator of the state vector.

### 7 The LOS Blocked Scenario

Half overtaking (with update rate of 20 ms) turns out to be
not so burdensome than full-overtaking. That is because right from the beginning, the TX car is
seen at different azimuth angles and close to the initial solution of (0,0) and the algorithm convergences fast. The regression model of [27] suffers from a strong bias due to the error correlation of the current observation and the regression matrix. The sequential algorithm outperforms the prior non-sequential modelling approach. The “errors-in-variables” approach comes very close to the error-free regression matrix. Furthermore, there is only a small loss to the nullspace projection. Keep in mind that the “error-free regressors” and the nullspace projection approach make use of exact (yet unknown), unquantized azimuth angles! The full overtaking manoeuvre is characterized by a difficult geometry. At the beginning the TX car is always seen at the same codebook in
and the algorithm struggles to converge. In this region the
algorithm is used to prevent divergence. After approximately 0.5 s, three different azimuth angles have been measured and the algorithm hands over to RLS. Even with an estimate of the initial state and the covariance matrix, the RLS algorithm needs a considerable time to converge afterwards. The situation is aggravated by the fact that the toughest part (TX car closest to RX car \(\rightarrow \omega_{\text{max}}\)) comes before convergence sets in. Nevertheless, an acceptable tracking result can be achieved here as well.

For an update rate of 50 ms the performance loss at “full-
over taking” is minor. In contrast, the previously simpler case of “half-overtaking” has now a larger performance loss. Due to the slower update rate, after only a few measurements, the overtaking car is already at steeper angles where the Doppler shift does not change so much and convergence is harder to achieve.

### 8 Conclusions

Geometric tracking of specular multipath components in ve
ricular millimeter wave channels is possible with low complexity algorithms. The proposed algorithm achieves good tracking even under very dynamic scenarios. This considerably relaxes
the time required for beam training. In addition, the proposed algorithm outputs a state vector that reflects the relative position and velocity of the multipath components. With this knowledge, it is possible to label the targets for onboard sensors as multipath components. This enables active learning for onboard sensors.

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50] ZENG Y, ZHANG R. Millimeter Wave MIMO with Lens Antenna Array: A New
Review Standardization of Fieldbus and Industrial Ethernet

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Biographies

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Erich Zöchmann (ezoechmann@gmail.com) received all his degrees (B.Sc., Dipl.-Ing., Dr.tech) in electrical engineering from TU Wien, Austria. From 2013 to 2015, he was a project assistant at the Institute of Telecommunications where he co-developed the Vienna LTE-A uplink link level simulator and conducted research on physical layer signal processing for 4G mobile communication systems. From 2015 to 2018 he was involved in experimental characterization and modelling of millimeter wave propagation. From November 2017 until February 2018, he was a visiting scholar at the University of Texas at Austin, USA. Besides wireless propagation, his research interests include physical layer signal processing, array signal processing, compressed sensing, and convex optimization.