Sensor Based Beam Tracking in Millimeter Wave Communications

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Abstract

The mobility management is of critical importance in millimeter wave communications. The directionality enforced by multiple-input-multiple-output (MIMO) and beamforming urges for a new paradigm of link maintenance in the 5G era. How to properly correct the direction choice from the mobile terminal in a real-time manner becomes a challenging problem with the dense deployment of 5G base stations. While the beam can be realigned with periodic trainings, the overhead is significantly large. To this end, an efficient sensor-aided technique for beam alignment is proposed. A thorough analysis with experimental data has been carried out for various scenarios, personal usages, and sensor fusion techniques. In addition to that, the performance of beam tracking has been analyzed. To overcome the misalignment caused by translation, in addition to rotation, a Kalman Filtering is used to track the direction of the base station by decoupling the translation and rotation in various motions. The tracking accuracy is further improved by reducing 50% of the alignment error. The proposed method is shown to reduce most of the beam training overhead in both outdoor and indoor scenarios.

I. INTRODUCTION

A. Motivation

Wireless network becomes an indispensable part of the society due to the connected world (Internet of Things (IoT), Machine to Machine (M2M) and social networks, et al). Meanwhile, with novel applications such as virtual reality, big data analysis, high definition video, and edge computing, etc., wireless data traffic is expected to increase at a rate of 50% over the next decade, and reaches 50 petabytes within the next five years.
Millimeter wave (mmWave) communication is a promising technology to meet the requirements and is considered as a cornerstone for the next generation of wireless mobile networks. Due to the short wavelength, the penetration and diffraction behaviors of mmWave communication deviate from the microwave counterpart. As a consequence, industry and academia investigated this area, and agreed that the technique of multi-input-multi-output (MIMO), especially beamforming, can compensate the link budget within small cells, by leveraging the compact antenna design given the short wavelength. Because the dimension of antenna array scales with the reciprocal of frequency, multiple antennas can be conveniently integrated on a board or chip to boost the antenna gains at both the transmitter and receiver. Leveraging this advantage, there is a radical paradigm change in the communication industry, where the omnidirectional communication is replaced by the directional one. The signal is thus “concentrated” toward some directions in trade for a better throughput. Therefore, a slight misalignment of beam could significantly degrade the system performance. As a result, the quality of the line of sight (LOS) link becomes the key to meet the link budget in the mmWave spectrum. The mobility in cellular communications significantly changes the pattern of system design, where both the resource management and mobility control need further discussions.

More specifically, unlike the military radar with an almost unlimited resource, only limited beam directions can be monitored simultaneously by both the base station (BS) and user equipment (UE) in civilian mobile networks. An omnidirectional design implies that it be ‘short sighted’ to every direction, as it incurs a high loss of antenna gain. The directionality means that the terminals are blind to a specific direction with a strong incoming signal during some period, which intensifies the probability of bilateral deafness without omnidirectional coverage. As a consequence, to maintain at least one workable beam in the mobile network, it requires
periodic updates and refinements for the beam selection, as illustrated in Fig. 2. It becomes more stringent to track the direction of signal when the beam becomes narrower.

When considering the above questions, the beam management in the 5G new radio (NR) system [1] is divided into four phases: beam sweeping, beam measurements, beam determination, and beam reporting. In general, the management in the above operations involves both periodic message exchange and event-driven reports. The first type of signal contains more structured reference signals for mutual sensing and handshake information. On the other hand, when an abnormal event or an abrupt environment change happens, an event-driven response could be required and generated by one end of the BS and UE. Then the other end measures and reports through the control channel to maintain the link. With a dense deployment in the 5G NR, the sudden link blockage occurs more frequently than the 4G long term evolution (LTE) system, and thus requires more frequent event-driven reports. This phenomenon could waste considerable system resources and nullify the benefits of the new spectrum. It is necessary to explore various approaches to reduce such overhead.

In a sharp contrast to the microwave communications where an environment of rich multipath is the foundation for the stochastic channel modeling, the propagation of mmWave signal is sparse and site-specific, depending on the geometry of the environment [2] [3]. As some research has indicated, the ray tracing could accurately characterize the channel modeling and design verification given an accurate environment model. Likewise, the information of location and orientation serves as an indicator of the potential beam direction and mitigates the challenge of beam tracking. An orientation-aware UE could proactively correct the beam direction based on the knowledge of its own attitude. Consequently, we study the beam management problem from an active tracking perspective.

Fig. 2: Initial access and beam tracking in beam management
B. Contributions

This paper mainly focuses on sensor-based beam management. The general idea is to determine the beam direction with the information collected from sensors in the UE, which is common in smart phones, after the initial access. We report the beam misalignment analysis based on field measurement, including the comparison between various types of motions. The major contributions of this paper are summarized as follows:

- We provide an overview of beam management and its relationship to the orientation estimation. In this work a great care has been taken to analyze the cause of beam misalignment, namely translation and rotation\(^1\).

- To the best of the authors’ knowledge, we are the first to verify the beam alignment of mmWave using both sensor measurements and optical benchmarks. Moreover, we extend our work to an open source dataset containing more motion measurements gathered by Michel from Tyrex Team, LIG, INRIA, which is available online\(^2\). In a contrast, most existing researches are based on pure simulations. The modeling of sensor cannot accurately characterize the real scenarios in our daily life. Based on the motion dataset, various motion types have a significant difference in the angle mismatch distribution. The tracking results with true benchmark provide valuable insights for the beam tracking algorithm design.

- Both compensation and prediction based beam tracking schemes are assessed under different applications. Contrary to the intuition, most sensor fusion algorithms have only a marginal advantage compared with simple sensor measurements. Meanwhile, to reduce the computational cost and boost the tracking rate, the prediction based beam tracking algorithm achieves a relatively more accurate tracking performance.

- We developed a Kalman Filtering algorithm based tracking mechanism to actively correct the beam misalignment, when the translation is a non-negligible factor in the tracking process. To this purpose, we propose an approximated linear ‘rotation’ factor to monitor the real-time translation as we observed in the experiment.

- We compared the overhead reduction in the beam management procedure in the framework of 5G NR. We accommodate all the tracking algorithms in the above tracking protocol with true measurements and 5G NR framework.

\(^1\)In this paper, we decompose a motion to translation, namely the movement of the centroid, and rotation around the centroid.

\(^2\)https://github.com/tyrex-team/benchmarks-attitude-smartphones
C. Organization

The remainder of this paper is organized as follows. Section II will briefly introduce how the orientation tracking assists the beam management in 5G NR communications and will cover the mathematical framework of orientation and beam tracking. Section III discusses both rotation-only and translation+rotation compensated beam tracking schemes. The former includes sensor based, sensor fusion and prediction based tracking algorithms. The latter further reduces the tracking overhead in short range communications. The compensation is still effective even without the knowledge of true positions of BS and UE. In Section IV, we describe the methodology of the dataset collection and how the benchmark and compensation schemes are compared. Section V contains detailed experimental results. It shows how various motion types and personal factors have distinct impacts on the angle mismatch for both indoor and outdoor scenarios, and then compares the tracking accuracy over multiple tracking schemes. There is also a comprehensive discussion on the performance of the translation-aware Kalman Filtering. Its performance is benchmarked against previous algorithms and is verified with an optical measurement system. The simulation of beam alignment overhead in 5G NR is compared over different motions and scenarios in Section VI. Finally, the conclusion is given in Section VII.

II. Background

As explained in the introduction, the mmWave communication relies on the antenna gain brought by the MIMO based narrow beam. The key challenge of directional communication is to control the beam direction to avoid outage [4].

A. Related Work

The beam management has been addressed in current mmWave WPANs and WLANs [5]. These protocols mostly feature a multi-phase beam tracking procedure, which is started by the coarse section-level sweep and is then refined. The typical situation of WLAN or WPAN is range and mobility limited. In the literature, a few attempts have been made to improve its efficiency in the mobility management. A perturbation-based tracking algorithm estimates the angle of arrival (AoA) in [6]. Meanwhile, the data packet also carries the channel condition information, which is explored in [7] as a stochastic optimization problem. These approaches prove themselves in the case of continuous movement, but may not address intermittent motions, which are quite common within our experimental record.
In addition, the steering direction can be found through the contextual information. Out-of-band signal [8] and light [9] [10] are two examples to correct their beam directions amid by additional information. In general, the mobile devices have a lighthouse to search for with these additional sensors. However, they suffer similar problems. First, it requires guidance from one additional system. Second, the signal processing has stringent computational requirements, which might be fairly power consuming. The last but not the least, they may become prone to blockages where the light cannot penetrate the obstacles.

However, there is a distinct difference between WLAN and mobile network, where a large number of roaming users exist within the network. The long period of beam training has already taxed significantly on the final throughput (48.6% overhead) [11], as both need to continuously monitor the transmission direction from both ends. This implies that the time of beam management in the mobile network be minimized, even with a dedicated control channel. Nevertheless, the 802.11ay attempts to mitigate the mobility with multiple users in [12].

The 5G NR beam management in the 3GPP specification defines a more dedicated and centralized control design. The typical implementation consists of both periodic reference signal and user-triggered training pilot in both downlink and uplink. The first type of reference signal called synchronization signal (SS) is sent toward the UE at a regular interval, with a predefined structure as shown in Fig. 3. Each SS burst contains multiple SS blocks and serves for initial access (IA) in the IDLE mode or periodic training in the connected mode. Each block will transmit toward one spatial area in a deterministic or random sequence to cover the whole cell. The number of SS blocks depends on the frequency band. Up to $N = 64$ SS blocks in the mmWave spectrum can be grouped into one 5ms SS burst to maximize the spatial coverage. When being connected, the beam tracking (BT) will utilize the Channel State Information Reference Signal (CSI-RS) or Sounding Reference Signal (SRS) to monitor the channel condition in the downlink and uplink, respectively. Comparing with the SS block of 4 OFDM symbols, the CSI-RS takes 1/2/4 OFDM symbols, and thus benefits the flexibility of dynamic length and further reduces the overhead. For the reverse propose, UEs will transmit multiple SRSs to the base station, in order to estimate the optimal available beam in a periodic, semi-persistent or aperiodic manner. The contextual information such as orientation and location could reduce the system overhead in a future deployment. To further reduce the overhead in the tracking procedure, we intend to steer the beam with IMU measurements without an explicit pilot signal.
B. Orientation Estimation and Beam Tracking

The measurement of orientation has been a critical mission for robotics, navigation, aerospace, and so forth. The earliest research could date back to the 1950s [13]. With the advancement of the integrated circuit (IC) technology, a self-contained inertial based integrated sensor, named inertial measurement unit (IMU), provides a low-cost solution to the measurement of self-attitude in the earth coordinate. Most of them consist of 3-axis sensors — gyroscope, accelerometer, and magnetometer. These sensors capture the angular velocity, earth gravity, and magnetic field respectively. Although none of these sensors can provide a long term reliable measurement, an optimal filter called sensor fusion yields a single estimation by combining the three measurements in order to reduce the impact of noise. Specifically, the typical approach is to integrate the angular velocity over time, which is captured by the gyroscope, and correct the accumulated drifting error with the other two sensors in the long term. Knowing its real-time attitude, the mobile device could effectively deal with the mismatch caused by mobility.

Several related works have attempted to address the beam tracking problems with sensors in the literature. In the study of human blockage and detection in WPAN systems, the authors have applied the sensor measurements for the event detection [14]. The research in [15] proposes an idea to predict the beam direction by sectionizing the spherical space, which is tested with sensor measurements. From the prospect of communication protocol, a sensor based beam tracking is proposed and tested with simulated sensor data [16]. Recently, authors in [17] discussed the feasibility with sensor measurement and analyzed the throughput with a synthesized signal strength heat map. The above researches have disclosed the potential of sensor-based beam management. However, most of the existing research is based on simulated sensor measurements.
with oversimplified sensor models. Moreover, the motions are assumed to be smooth without abrupt rotation. Last but not the least, it is more interesting to see whether we could benefit from sensor fusion algorithms. We need more evidence to see if it stands right on the time scale of wireless communication (sub-seconds).

Depending on the density of obstacles and the user mobility pattern, channel modeling shows that outages on an mmWave link may occur with a significant probability of 20%-60% [18]. The moving obstacles, foliages or buildings in the volatile environment cast an intermittent shadowing on the mmWave communication channel. When the channel encounters an abrupt change, the mobile station must initiate the IA process to seek a reflective path or backup base station. This high frequency of switching between LOS and NLOS puts questions on the need for long-term beam tracking without IA. Considering that gyro is relatively accurate in the case of short-term tracking, we should re-examine this idea with real measurements.

Accounting for observations above, we evaluate the sensor-based beam tracking by the beam misalignment angle. The mismatch due to motion can be decoupled into two components, namely the translation and rotation. Between these two, the rotation is identified as the leading factor for the angle mismatch in a short time duration in the LOS condition. Even with a narrow beam, the area covered by the beam is sufficiently wide with a reasonable distance. For instance, given a 3° half-power beam width, the cone spans up to 5.23m at the distance of 100m, which converts to roughly 3.50s corresponding to the human walking speed. Even for high-speed vehicles (120km/h), the beam selection stays valid for 156ms. On the contrary, the story is much different for the rotation, since up to 70° rotation can be achieved within 1 second in our daily life, as reported in [8]. To maintain a robust connection, the mobile device requires substantial training overhead with a high rotation rate.

C. Coordinate System and Lie Group

Before we proceed to the experiment and algorithm, we briefly introduce the coordinate we used in this paper and mathematical background on the representation of orientation.

1) Coordinate Systems: In this paper, we adopt two coordinate systems from the 3GPP standard, namely the global coordinate system (GCS) and the local coordinate system (LGS), such that the discussion is within one unified framework. The first system accommodates all BSs and UEs and is considered to be permanently invariable during simulation. In this coordinate, each system component is defined by a location \((x, y, z)\) and direction vector \((\Theta_{azi}, \Theta_{ele})\), where
the subscripts means Azimuth and Elevation. This direction vector represents the radioactive pattern of the antenna array. In a contrary, one LGS is created and attached to each component, where the relative locations and directions of other components can be pursued by rotation and translation. For the transformation of all motions, it is decomposed to translation and rotation. Translation is a simple vector addition for any point \( p = (x, y, z) \). However, the rotation needs a more dedicated definition.

2) Rotation Representation via Lie Group: In \( \mathbb{R}^3 \), the rotation operation is a linear transformation that reserves the length and relative position around the origin. The group \( SO(3) \) can be studied as a Lie group \( G \), which is closed on the product and inversion in group theory and owns a structure of the differential manifold. The parameterization of such a group is an unsettled problem as many representations exist in the literature, and each owns their unique advantages. The Euler angle has the lowest-dimension and is easy to comprehend, while it suffers from the singularity such as the Gimbals lock \[19\]. The rotation matrix is also a popular choice in many faces of rotation. The orthogonal property of the rotation matrix imposes 6 constraints on 9-dimensional parameterization. The comparison of these methods is not the focus of this paper. We choose a four-element representation, namely the quaternion, over other options.

The quaternion is a generalized concept of complex number in the 4-dimensional space \[20\], i.e. in the form of \( q = a + bi + cj + dk \), where \( a, b, c, \) and \( d \) are real numbers and \( i, j \) and \( k \) are imaginary units. The imaginary parts satisfy \( i^2 = j^2 = k^2 = ijk = -1 \), \( ij = k \) and \( ji = -k \), which renders it non-commutative in multiplication. To represent the rotation operation, the quaternion is constrained to have a unit norm \( \|q\| = 1 \) as a sphere in the 4-dimensional space\[2\]. The reverse rotation of \( q \) is its conjugate \( q^* = q = a - bi - cj - dk \). Then the well known formula for rotation operation \( R(d) \) on a vector in 3D space with quaternion \( q \) has the following form:

\[
R_q(d) = \bar{d}' = q \otimes \bar{d} \otimes q^*,
\]  

where \( \otimes \) is the quaternion multiplication. The \( \bar{d} = 0 + d_x i + d_y j + d_z k \) is a pure quaternion of \( d \) with the real part \( a = 0 \). Please refer to \[21\] for more details of quaternion.

3) The Tangent Space of \( SO(3) \): The quaternion enjoys many advantages, such as easy for interpolation, robust to rounding error and singularity-free, while it does not satisfy the simple

\footnote{The degree of freedom in the rotation quaternion \( q \) is three as it is a unit quaternion. The forth elements can be uniquely determined by the other three elements.}
vector addition + as a standard vector space. This constraint hinders its application in an ordinary Kalman Filtering (KF). By the diffeomorphism on the Lie group, every Lie group $G$ is associated with a vector space called Lie algebra $so(3)$ endowed with a bilinear Lie bracket $[\cdot, \cdot]$ [22]. This vector space represents the tangent space of the origin of $G$ and retains local information. In details, this vector space is in the form of

$$so(3) = \{ M = V^\wedge \in \mathbb{R}^{3x3} | V \in \mathbb{R}^3 \}$$

where

$$M = V^\wedge = \begin{bmatrix} V_1 \\ V_2 \\ V_3 \end{bmatrix}^\wedge = \begin{bmatrix} 0 & -V_3 & V_2 \\ V_3 & 0 & -V_1 \\ -V_2 & V_1 & 0 \end{bmatrix}$$

where the $^\wedge$ operation is a mapping from $\mathbb{R}^3 \rightarrow so(3)$ and $^\vee$ is the reverse operation. Now the skew-symmetric matrix can be generated from a 3-dimensional vector $V \in \mathbb{R}^3$.

Given the above definition, the connection builds upon the exponential and logarithm map as follows:

$$\mathbb{R}^3 \rightarrow so(3) \rightarrow SO(3)$$
$$\mathbb{R}^3 \rightarrow S^3 : \quad q = \text{Exp}(V)^\wedge = e^{V/2}$$
$$SO(3) \rightarrow so(3) \rightarrow \mathbb{R}^3$$
$$S^3 \rightarrow \mathbb{R}^3 : \quad V = 2\text{Log}(q)^\vee$$

The constant 2 in above equation can be derived by the differentiation of Eq. (1). The detailed explanation of mapping can be better explained by the axis-angle theory, which is a topic beyond the scope of this paper. Interested readers could find more materials in the book [20]. Given such a vector, we have an alternative route that the KF builds upon without any compromise on the quaternion.

4) Gaussian Distribution in $SO(3)$: The KF is the optimal filter when the noise is modeled as a Gaussian one. Similar to a Gaussian random variable $x \sim \mathcal{N}(\mu, \Sigma)$, the Gaussian distribution over the 3-dimensional rotation is defined with the expectation $\mu$ in $SO(3)$ and covariance $\Sigma \in \mathbb{R}^{3x3}$. Sampling from such a distribution is a non-trivial task. One realization $q = \text{Exp}(\varepsilon) \otimes q$ is decomposed by the expectation $q = q\text{Exp}(\mu) \in SO3$ and a small ‘disturbance’ $\varepsilon \sim \mathcal{N}(0, \Sigma)$ with a left multiplication. In addition to that, the composition of two uncorrelated Gaussian distributions $(q_1, \Sigma_1)$ and $(q_0, \Sigma_0)$ is defined as:

$$(q, \Sigma) = (q_1, \Sigma_1) \circ (q_0, \Sigma_0) \sim (q_1 \otimes q_0, \Sigma_1 + J(q_1) \cdot \Sigma_0 \cdot J(q_1)^T).$$

(5)
where $J$ is the Jacobian matrix of $q$.

### III. SENSOR-AIDED BEAM TRACKING DESIGN

In this paper, we propose to compensate the angle mismatch in the beam tracking using the measurement of motion sensor in two scenarios. Informally speaking, the fundamental difference is the distance between BS and UE, which determines whether the rotation will be significant. The angle mismatch with a large propagation distance in the outdoor environment is dominated by the rotation-caused mismatch. Contrary to that, without the compensation of translation, the communication link will be more vulnerable to the angle mismatch in the indoor scenario. We are also aware of the NLOS scenarios, which can be generalized to the indoor case, when the NLOS signal is reflected at the obstacles close to the receiver.

![Fig. 4: Illustration of timing structure in the beam tracking](image)

A. Rotation-Only Beam Tracking

We first discuss the beam tracking subject to only rotations, which is the major concern of beam tracking.

1) Compensation Scheme: The scheme of sensor-based tracking approach is shown in Fig. 5, whose timing structure is illustrated in Fig. 4. First, we assume that the beam is perfectly aligned after the IA procedure at $t$. Then each IA contains at most $n$ BT periods, each of which is denoted by $dt$. The UE actively corrects its beam direction $d_{LCS}(t)$ in LCS, which is given by

$$\bar{d}_{LCS}(t + \Delta t) = \Delta q(t)^* \otimes \bar{d}_{LCS}(t) \otimes \Delta q(t),$$  \hspace{1cm} (6)

where $\Delta t = kdt$ and $1 \leq k \leq n$. As defined in (1), $\bar{d}_{LCS}$ is the pure quaternion of beam direction $d_{LCS}$. In this scheme, the correction amount $\Delta q(t)$ is provided by various compensation
If the correction amount \( \Delta q(t) \) is acquired through the gyro measurement, then it is a production given by

\[
\Delta q(\Delta t) = \Delta q_k(dt) \otimes \Delta q_{k-1}(dt) \otimes \cdots \otimes \Delta q_1(dt)
\]

over \( \Delta t \). Specifically, given the angular velocity \( \omega_l(k) = (\omega_x(k), \omega_y(k), \omega_z(k)) \), the quantity of rotation \( \delta q(k) \) is given by

\[
\delta q(k) = \cos \left( \frac{\delta t l}{2} \right) + \frac{i}{l} \omega_x(k) \sin \left( \frac{\delta t l}{2} \right) + \frac{j}{l} \omega_y(k) \sin \left( \frac{\delta t l}{2} \right) + \frac{k}{l} \omega_z(k) \sin \left( \frac{\delta t l}{2} \right),
\]

where \( l = \|w\| \).

Otherwise, we take the rotation incremental \( \Delta q(t) \) during the time \( \Delta t \), estimated by sensor fusion algorithms. This correction procedure continues until the next IA, or the mismatch is beyond the beam width requirement.

![Beam tracking procedure](image)

Fig. 5: Beam tracking procedure assisted by the motion sensor.

2) Prediction Scheme: The above tracking scheme compensates the beam direction during the time \((t, t + dt)\) given the measurement at \( t \). The period of measurement is proportional to the tracking latency in this process, when the sampling rate is not sufficiently high. Aside
from the rapid response, the power consumption with high frequency sampling raises concerns of draining the battery too soon in the mobile device. Take 5G NR as an example: the minimum scheduling unit (named slot) is as small as 0.125ms. With a 100Hz sensor based tracking system, each period between samples contains as many as 75 slots. Therefore, to overcome the above defects, we propose to steer the beam actively in a predictive approach\(^3\). By up-sampling the angular velocity and then interpolating the measurements in a finer time step \(\delta t\), the beam direction between \((t, t + dt)\) attains periodic updates with rotation \(q(\delta t)\) in finer granularity.

**B. Beam Tracking with Translation Compensation**

The second major cause of angle mismatch is the translation of the UE’s centroid, which is significant for short range communications. To address the tracking issue in the ray-tracing technique, which is an accurate geometric model of the wireless channel, the locations of UE and BS are the prerequisite for the AOA searching. Among them, the environmental model can be downloaded on-the-fly or pre-loaded as an offline data. The location estimation requires an accurate GPS signal for large scale localization and the integral of accelerometer for small scale movement. However, the complexity stems from the randomly moving objects, where blockages and reflections occur unexpectedly and cause trouble for the modeling.

To address the above issues, we assume that the translation roughly has the same speed and direction in a short period. Indeed, as we will see in Section V, the angle mismatch shows a steady and linear increasing relationship with time, meaning that the translation-caused mismatch rate keeps unchanged. As a consequence, this factor can be approximated as a rotation component. Thus we propose an extended Kalman Filter (EKF) based beam tracking scheme. Similarly to the standard EKF, this beam tracking scheme is divided into two phases, prediction and update, in a recursive manner. The elements of EKF are explained as follows.

1) State Vector: We consider the state vector \(X(t)\) consisting of the beam direction \(d_{LCS}(t)\) and a translation-caused rotation quaternion \(q_t(t)\) (here the subscript \(t\) means translation) over \((t, t + 1)\). Note that the definition of beam direction does not follow the traditional elevation and azimuth angles \(\Theta_{azi}\) and \(\Theta_{ele}\) in the antenna theory. The main reason is to

\(^3\)The highest sampling rate of a typical IMU sensor could reach 8000Hz according to the reference manual [23]. However, the sensor rate provided by the operating system is limited to 100Hz, and high-frequency measurement could be noisy, when an internal filter is bypassed.
reduce the complexity with the derivation of the Jacobian matrix and its computation. We take a 3-dimensional unit vector as the direction for its easy normalization and simple addition. Combined with \( q_t(t) \in \mathbb{R}^4 \), the state vector is \( X \in \mathbb{R}^7 \). The system input \( U(t) \) characterizes the rotation operation \( R_r \) provided by the gyro measurement \( \omega \) as in Eq. (8).

2) Prediction Equation: The state prediction at time \( t + 1 \) is propagated via the system model given by

\[
\begin{align*}
\dot{X}(t + 1) &= \begin{bmatrix} d_{LCS}(t + 1) \\ q_t(t + 1) \end{bmatrix} = f(X(t), U(t)) + W(t) \\
&= \begin{bmatrix} R(d_{LCS}(t)) & 0 \\ 0 & I \end{bmatrix} X(t) + \begin{bmatrix} W_d(t) \\ W_q(t) \end{bmatrix} 
\end{align*}
\]

where \( R(d_{LCS}) = R_t(R_r(d_{LCS})) \) is the combination of both the rotation \( R_r \) and translation \( R_t() \) as in Eq. (1) on the beam direction \( d_{LCS} \). As the KF does not preserve the unit-norm constraint imposed on the estimated quaternion \( q_t \), we will treat the addition in the tangent space of \( SO(3) \) as we explained in Section II-C2. We further assume that the process noise follows the zero-mean Gaussian distribution, namely \( W(t) \sim \mathcal{N}(0, Q) \), in which \( Q \sim \text{diag}(\Sigma_d, \Sigma_q) \in \mathbb{R}^{6 \times 6} \) because the Gaussian distribution is now in the vector space of \( so(3) \).

Meanwhile, the process covariance \( P \) propagates as follows:

\[
P_{t+1|t} = J_{t+1|t} P_{t|t} J_{t+1|t}^T + Q_t 
\]

where \( J \) is the Jacobian matrix of system predictive model and \( Q \) is the process noise covariance \( \mathbb{E}(W(t)W^*(t)) \).

3) Measurement Equation: The measurement is available when the next IA is initialized or explicit beam tracking is required. The measurement equation is given by

\[
\begin{align*}
Z(t + 1) &= \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} X(t + 1) + \begin{bmatrix} V_d(t) \\ V_q(t) \end{bmatrix} 
\end{align*}
\]

where measurement \( Z \) can be observed directly. The measurement noise \( V(t) = (V_d(t), V_q(t)) \) also follows the Gaussian distribution \( V(t) \sim \mathcal{N}(0, \Sigma_R) \).

As we explained in the background of beam management, the beam direction \( d_{LCS} \) is recalibrated by the IA procedure. After that, the UE will keep tracking this direction unless the obstacles corrupt the link. As for the measurement noise \( V_d \), the probability of one
sub-optimal beam choice is made nonzero by the IA. Nevertheless, no second chance is available until the next IA, and the UE will stick to this sub-optimal beam selection during this period. Consequently, we trust the beam selection with the highest confidence.

To measure the translation-caused rotation, we notice that the total rotation is equivalent to the residual angle mismatch after the rotation-only compensation. In particular, the mismatch $R_t$ is the accumulated rotation $q_t(\Delta t)$ over the measurement period (the IA period) $T_{IA}$, which is equal to the angle mismatch between the updated beam direction $d(t)$ and gyro compensated beam direction $\hat{d}(t)$ shown as the orange angle in Fig. 5. In details, this rotation quantity is defined as

$$q_t(\Delta t) = \left[ (\sqrt{||\hat{d}(t)||^2} \ast ||d(t)||^2 + \hat{d}(t) \cdot d(t)), \hat{d}(t) \times d(t) \right] \times [1, i, j, k]^T \quad (11)$$

In many cases we are interested in the scenario in which the period of beam tracking $dt$ is much less than the IA period $T_{IA}$. Without loss of generality, we assume that the measurement period $T_{IA}$ and prediction period $dt$ of KF satisfies $n \cdot dt = T_{IA}$.

In such a case, the measured state $q_t(\Delta t)$ needs to interpolate the residual angle mismatch in Eq. (11) with the interpolation factor $1/n$ by the spherical linear interpolation (SLERP) algorithm. The noise $V_q$ is determined by the gyro measurements.

4) Measurement Update: After a measurement is supplied after IA, we will merge the measurement and predicted states through the Kalman gain. Here we list these update equations as below and explain in details.

**Kalman Gain:**

$$K_t = \begin{bmatrix} K_{1t} & 0 \\ 0 & K_{2t} \end{bmatrix} = P_{t|t-1}(P_{t|t-1} + R_t)^{-1}$$

**Measurement Residual:**

$$y_t = \begin{bmatrix} y_{dt} \\ y_{qt} \end{bmatrix} = Z_t - H_t \hat{X}_{t|t-1} = \begin{bmatrix} d_{LCS} - \hat{d}_{LCS} \\ (q_t \otimes q^*_{t|t-1}) \end{bmatrix}$$

**State Update:**

$$\hat{x}_{t+1|t+1} = \hat{x}_{t+1|t} + K_{t+1}y_{t+1} = \begin{bmatrix} d_{LCS} \\ \text{Exp}(K_{2t} \cdot 2\text{Log}(y_{2t}))^\wedge \otimes q_{t|t-1} \end{bmatrix}$$

**Covariance Update:**

$$P_{t+1|t+1} = (I - K_{t+1})P_{t+1|t}(I - K_{t+1})^T + K_t R_t K_t$$

(12)

Because the measurement matrix $H$ degrades to an identity matrix $I$, the Kalman gain $K$ is simplified as above, where $P_k \in \mathbb{R}^{6 \times 6}$ and $R \in \mathbb{R}^{6 \times 6}$ are the error covariance matrix and measurement covariance matrix, respectively. The inconsistency between the state and covariance is due to the mapping between the Lie algebra and quaternion. With the quaternion state, the notation $\otimes$ means the quaternion multiplication $\otimes$ of conjugate $q_{t|t-1}$. As we have assumed that the measurement of beam direction is perfect, in the state
update formula the Kalman gain $K$ will force the state $\hat{x}_{t|t}$ to equal the measurement $d_{LCS}$ due to the IA mechanism given that the measurement of beam direction is perfect. The translation-caused rotation is updated as a small disturbance $\text{Exp}(K_{2t} \cdot 2\log(y_{2t})^\wedge)$ on a mean quaternion $q_{t|t-1}$. Finally, the estimation covariance $P_{t|t}$ is updated accordingly.

In conclusion, we present three beam tracking schemes, namely pure rotation compensation, rotation prediction and rotation-translation prediction, from most simple rotation schemes to the translation-aware approach. Considering the computational complexity, we will examine them with measurements collected from field experiments in the next section.

IV. Experiment Methodology

In this section, we present the methodology of experiments, which make use of both IMU sensor record and optical tracking system. Two datasets are used in this paper:

- **UTK dataset**, which is obtained by the authors in the University of Tennessee Knoxville (UTK) using IMUs in Iphone 7 and optical measurement.
- **Tyres dataset**, which is an open dataset collected by the Tyres team in INRIA.

These two datasets share most of the similarities, except for the difference in the sampling rate, which will be elaborated later. Although the second dataset contains more comprehensive and elaborated records, its goal is to compare the performance across various sensor fusion algorithms, where only the relative angle mismatch is important. However, in our case, the beam tracking requires an accurate benchmark to compare with, especially in Section VI. Therefore, we first conduct our own experiment to obtain the UTK dataset, provide a preliminary result and ensure the accuracy of the conclusion. With the second dataset, we explain the general setup and how the benchmark and sensor data are gathered and prepossessed for the comparison of tracking algorithms.

A. IMU Measurements

The performance of IMU sensors depends on the cost. A high-end gyroscope only drifts $0.001^\circ/h$, while a low-cost one could be $0.1^\circ/s$. As we intend to study the beam management of the mmWave communication in volumetric commercial devices, it is critical to collect the measurements with IMU in off-the-shelf mobile phones. In both datasets, the measurements are sampled with the frequency of 100Hz through the operating system of smart phone. It introduces an unpredictable latency, which can be observed through the timestamp in the final record.
However, for the offline processing, these negative impacts can be corrected correspondingly. One more thing to be noticed is that most operating systems provide two sets of measurements, namely raw and calibrated measurements. As shown in [24], the uncalibrated raw measurement is polluted with bias and unbalanced scaling factors between the axes. These measurements create an inconsistent orientation estimation when being fed to the sensor fusion. We use raw measurements for the sensor-based approach. Meanwhile, calibrated measurements are applied in various beam tracking algorithms.

B. Optical Measurements

The technique of optical tracking system helps to provide an accurate reference for human motion capture in the literature and is considered as the standard benchmark for the sensor fusion research. In our test, an Optitrack system, consisting of multiple infrared cameras connected to one single laptop, is applied to capture the precise Cartesian position of the infrared reflective marker in a room of $4m \times 6m$ [25]. All the cameras are carefully placed on the roof, each pointing to the center. The system is initialized and calibrated with a reference triangle and three rods mutually orthogonal to guarantee the tracking accuracy. To resolve the orientation and position of the mobile device, we fix a three-axis rod rigidly on the phone case with markers on the tips, as shown in Fig. 6(b). As the data sheet being provided, the accuracy of position is less than $\pm 0.1mm$ when being correctly tracked. In our experiment, the tester holds and operates the cell phone walking or sitting on a chair, and its position is logged by the optical tracking system at the rate of 100Hz to match the IMU sampling rate. In contrast, the sampling rate in the Tyrex dataset is set to 60Hz. As a result, resampling is necessary for the preprocessing procedure to generate the benchmark position and orientation according to the timestamps as in Fig. 7.

C. Benchmark of Trajectory and Beam Direction

The benchmark, as the correct answer to the positioning and optimal beam direction, is based on the optical system above. In the calculation, the mobile device and rods are considered as a rigid body without deformation. Moreover, the infrared markers are fixed on the tips with adhesive materials and deliberately arranged to represent the sensor coordinates as shown in Fig. 6(b). $A_g$, $B_g$ and $C_g$ denote the corresponding global positions of markers $A$, $B$, and $C$.

In this paper, we take a semi-realistic setup for the benchmark calculation, as we assume the position of the base station. In details, we have the following three steps:
1) Trajectory: The position (the center point) of antenna array center is defined as the middle point of rod, where \( GCS(t) = \frac{A_g(t)+C_g(t)}{2} \).

2) Orientation: We first define the orientation of the cellular phone as the three axis rods \( \vec{X}_g-\vec{Y}_g-\vec{Z}_g \) in the global frame. The \( \vec{X}_g \) axis is defined as \( \vec{X}_g = \frac{A_g-C_g}{\|A_g-C_g\|} \). Then \( \vec{Y}_g \) is found based on the central point \( M \), \( A_g \) and \( C_g \). It satisfies \( \vec{Y}_g = \frac{B_g-M}{\|B_g-M\|} \perp \vec{X}_g \) to maintain the orthogonality between the \( \vec{X}_g \) and \( \vec{Y}_g \) axes of cellular phones’ orientation. The third axis \( \vec{Z}_g \) is given by the cross product \( \vec{Z}_g = \vec{X}_g \times \vec{Y}_g \). Comparing with the global coordinate, we can obtain the quaternion of the orientation.

3) Beam Direction: With the location of static BS \( BS_{GCS} = (x, y, z) \) in the assumption and trajectory \( M_{GCS}(t) = (x(t), y(t), z(t)) \) of UE in the global frame, the optimal beam direction \( d_{opt}(t) \) is defined appropriately as \( d_{opt} = \frac{M_{GCS}(t)-BS_{GCS}}{\|M_{GCS}(t)-BS_{GCS}\|} \). Considering that the UE steers its beam based on its local information, this global direction is converted to the UE’s local coordinate for comparison with compensated beam.

### D. Comparison Baseline

The strategies we applied in the section of experimental results are listed as follows:

- No compensation: This allows us to understand the behavior of angle mismatch over time.
• Gyro Based Compensation: It uses the raw sensor measurements to compensate the beam direction. This provides the baseline of sensor-based tracking and has a minimum requirement on the computational resource.

• Sensor Fusion Based Compensation: In this approach, multiple sensor fusion algorithms provide the correction quantities to the UE based on the calibrated sensor measurements, and the attitude update is compared correspondingly.

• Kalman Filter with Translation Compensation: This is the method we discussed in III-B, which takes the translation into account.

• Optical Benchmark: This provides the baseline of the optimal rotation tracking. The attitude is resolved by the optical system, which fully compensates the rotation-caused beam misalignment.

Besides the comparison of the compensation, we also analyze the benefits by up-sampling the sensor measurements to provide better tracking accuracy.

E. Performance Metric

The performance metric in this paper is the angle mismatch during the beam tracking procedure. We compare the angle mismatch defined in the LCS. In particular, the beam deviation between the true orientation $d_{\text{opt}}(t)$ and compensated beam $\hat{d}_t$ is given by

$$\delta d(t) = |\arctan \left( \frac{||d_{\text{opt}}(t) \times \hat{d}_t||}{d_{\text{opt}}(t) \cdot \hat{d}_t} \right)|.$$  \hfill (13)

Note that this mismatch is non-negative due to the reason that the angle is defined as the shortest angle mismatch on the unit sphere.

![Fig. 7: Resampling of optical measurement, time alignment and bad sampling removal](image-url)
1) Implementation Details: The following two issues will be addressed in the data analysis as in Fig. 7:

- Time Alignment of Two systems: In order to compare the benchmark and compensated directions, the time synchronization of two systems plays a key role in the final results. Without the same clock, we seek the time difference to align the two records. Our record has a two-phase design. At the beginning of each record, the UE is raised for three times in the Z-axis. This pattern is taken for a rough time alignment. Then we refine the records with a rotation angle by the first $\frac{1}{10}$ of record. With the time granularity of 1ms, $t_{adj}$ is determined such that the correlation of Euler angle is maximized. Correspondingly, the default alignment method in the dataset [26] is aligned with the acceleration record. Comparing the same motion type (walking) of two datasets, we are aware that the default alignment creates a larger angle mismatch over time, which means that the default method is interior. Herein, we re-calibrated the $t_{adj}$ among all the motions of all datasets.

- Bad Samples: The second problem is that some bad samples exist in the benchmark records, where the position of tracking markers is unavailable, or the precision is not sufficiently good. This leads to a missing attitude in the benchmark record. To minimize the effect, we abandon the comparison results in a neighborhood of the bad record time.

V. DATASET ANALYSIS AND EXPERIMENT RESULT

In this section we first present the observation of the beam mismatch, and then provide a detailed discussion about all the compensation strategies with subsampling time prediction. In the following discussion, all the results are discussed with two scenarios, namely outdoor and indoor. Here we assume that the IA period is adjusted to 200ms unless mentioned otherwise. Based on the knowledge of authors, this setting could cover both the maximum SS-Burst in 5G NR or beacon interval in the 802.11ad. The base station is assumed to hang at the height of 20m with a distance of 100m to the UE. For the short-range communication scenario, the BS is placed on the top of the meeting room at the height of 3m. We mainly focus on three performance criteria to evaluate the compensation result.

- The cumulative distribution function (CDF) for an intuitive comparison.
- The mean value with a 95% empirical confidence interval.
- $P95 = \{\theta | CDF(\theta) = 0.95\}$, which is the 95% percentile of the CDF, to provide a better insight of upper bounds of mismatch.
A. Preliminary Result of Beam Mismatch

We first present the CDF results of our experiment. The main goal is to validate the methodology in the timestamp alignment and interpolation. If comparing it with the CDF, one finds that the angle mismatch is in the same range, especially for the walking motion.

![CDF of Angle Misalignment](image)

Fig. 8: UTK dataset—comparison of CDF of angle mismatch: no compensation and Gyro

B. The Mismatch without Compensation

As illustrated in Figures 9(a) and 9(b), the CDFs of different motions, represented by the solid line, can be divided into two groups. The gentle motions have similar CDFs with small angle deviations. The other three motions (running hand, running pocket and swing) have distinct distributions in the angle deviation. This trend also holds for indoor scenarios.

The detailed numerical results can be found in Table I, showing all the mean values and $P_{95}$ across all motions.

1) Impact of Personal Behaviors and Various Devices: Before we proceed to other methods, we need to investigate whether the user behaviors and devices cause significant variances in the CDF. From Table I, the user behavior has distinct fingerprints, as the order of mismatch is different among users. For instance, the running pocket has more mismatch compared with swing of user 1; yet the order is reversed for user 2. On the contrary, we observe a similar order of mismatch magnitude among IMU measurements of Iphone 4, Iphone 5 and Nexus 5 with users.
Fig. 9: Tyres dataset—CDF of angle mismatch among different motions: uncompensated

C. Gyro-based Compensation

Nevertheless, motivated by the above observations, we further provide the mismatch results compensated by the gyro measurements compared with the optical benchmark and uncompensated in Fig 10. These comparisons provide promising insights concerning the motion and distance. In general, we can observe that the maximum mismatch is below $5^\circ$ for most of the motions. There is only one exception, namely the indoor intense motion, where the gyro-based compensation fails to meet this upper bound. We remark that these errors are due to the translation of the UE centroid in this specific scenario. Moreover, this simple compensation strategy may have an inferior performance due to the noise and nonlinear truncation, in which we are interested in further improvement. Fig. 10 shows these marginal gains that we expect when the rotation is perfectly compensated. Since the tracking accuracy of the optical system is around $1^\circ$, the result demonstrates that the rotation compensation error is well bounded by $1^\circ$.

Another interesting result shown in Fig. 11 is that the mismatch grows linearly in most cases. It is interesting to observe that the deviation increases linearly in most cases. This trend confirms that the residual errors are caused by the translation of centroid, which can be approximated by a linear translation over a short period.

In conclusion, the use of motion sensor such as gyroscope enables the efficient beam tracking without explicit training. It confirms our assumption in Section II; i.e., the rotation is responsible for most misalignments in most cases. Considering the physical limitation and power consump-
Fig. 10: Tyres dataset—mean value and 95% confidence interval of various motions: uncompensated, Gyroscope compensation and optical benchmark

Fig. 11: Tyres dataset—P95 angle mismatch over 200ms

tion, a mobile device will not have a sharp narrow beam with a practical antenna array, which means that most of the translation-caused mismatches will be covered in short times. The second breakthrough to reduce the tracking mismatch is the compensation by translation. However, this may require an accurate environmental modeling.

D. Sensor Fusion Based Compensation

In theory, sensor fusion algorithms provide more accurate orientation estimations, where the drifting of the gyroscope is corrected by the accelerometer and magnetometers periodically. The
TABLE I: Tyres dataset—mean and P95 of Angle Mismatch

<table>
<thead>
<tr>
<th></th>
<th>Person 1</th>
<th>Person 2</th>
<th>Person 3</th>
<th>Person 1</th>
<th>Person 2</th>
<th>Person 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outdoor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>2.8255</td>
<td>3.9829</td>
<td>17.122</td>
<td>13.145</td>
<td>2.8152</td>
<td>15.731</td>
</tr>
<tr>
<td>Indoor</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>5.3788</td>
<td>23.352</td>
<td>16.689</td>
<td>12.253</td>
<td>5.6115</td>
<td>18.351</td>
</tr>
<tr>
<td>P95</td>
<td>9.4867</td>
<td>45.585</td>
<td>31.368</td>
<td>33.5</td>
<td>18.33</td>
<td>49.902</td>
</tr>
</tbody>
</table>

latter two sensors need low-pass filters to extract the direction of gravity and magnetic north pole from measurements polluted by high-frequency noise. However, the short-term sensitivity is mostly determined by the gyroscope, which leaves an open question for sub-second tracking accuracy. In this paper, the rotation compensated by the sensor fusion algorithms is calculated as the incremental of orientation estimation, namely

\[ \Delta \hat{\mathbf{q}} = \hat{\mathbf{q}}_t \otimes (\hat{\mathbf{q}}_{t-1})', \]  

(14)

if \( \hat{\mathbf{q}}_t = \Delta \hat{\mathbf{q}} \ast \hat{\mathbf{q}}_{t-1} \). The parameter tuning is beyond the scope of this paper. Thus we use the default hyper-parameters in [26].

Fig. 12 depicts the comparisons between the optical benchmark, gyro and sensor-fusion algorithms over all the motions. This figure shows the observation that no dominant performance advantage is achieved by the sensor fusion algorithms. More specifically, the fusion algorithms have only marginal improvements against gyro compensation in some motions, whereas this does not hold for all motions and scenarios. Moreover, none of these algorithms could close the gap to the optical benchmarks. This result can be explained by the mechanism of sensor fusion mentioned above, where the nonlinear clap on the range of gyro measurements limits the accuracy. As a consequence, the computational cost of sensor fusion algorithms outweighs these marginal benefits. Instead of perfecting the rotation compensations, we suggest to tackle the translation-caused angle mismatch to further reduce the overhead, especially in the short-range communications.

E. Compensation vs Prediction

Limited by the sampling granularity of the optical benchmark system, we demonstrate the prediction based tracking in a reverse approach. We first down-sample the IMU measurement
Fig. 12: Tyres dataset—comparison of mean angle mismatch using various compensation strategies: person 1

from 100Hz to 50/25Hz. Then we redo the up-sampling and use the predicted "measurement" to correct the beam direction between the down-sampled measurements. In this case, the ground truth takes the benchmark result in 100Hz. For the period of 20ms (40ms) in Fig. 13, the beam direction is perfectly aligned at each time $t$. Then the predicted performance is compared with benchmarks at time 10ms (30ms). For gyro-based prediction, the incremental approach is a simple integration over $\Delta t = 10, 20, 30$ms, while the second type, the sensor fusion scheme, uses the spherical linear interpolation (SLERP) algorithm [27].

Fig. 13: Tyres dataset—prediction of beam tracking scheme.

As can be observed in Fig. 14, leaving a beam unattended within one period is not a wise approach for the beam tracking. By proactively steering the beam direction, the performance is competitive with a The improvement over mismatch is evident among all scenarios and sampling rates. For the
outdoor situation as shown in Figures 14(c) and 14(d), all mismatches reduce to at most one-third of the uncompensated scene, while more residual mismatches are present due to the translation. With this predictive approach, both power consumption and tracking error are minimized. Once again, no apparent advantage shows along sensor fusion algorithms.

Given all the observations and results up to now, we conclude that, by combining the sensor-based compensation on the sample scale with prediction adjustment on the sub-sample scale, this tracking algorithm provides the optimal tradeoff on the beam tracking performance among all the options. Note that we do not mean that the sensor fusion algorithm does not work. Its merits are more appreciated in the long time orientation tracking at a time scale (minutes or hours) much more significant than a typical initial access period (sub-second).
Herein, we consider it sufficient to track rotation with raw sensor measurements; hence our next target is to eliminate the mismatch caused by the translation.

**F. Beam Tracking with Translation Compensation**

Within the same framework as we explained in Section IV, we compare the angle mismatch when the measurement period \( T_m = 16T_p \). As can be observed from Fig. 15, both indoor and outdoor situations benefit from our method. This translation-aware tracking algorithm reduces the angle mismatch compared with the benchmark result. Now, even for the indoor case with intense motion, the mean of tracking mismatch is controlled under 5°. Meanwhile, the confidence interval shows a significant improvement. As discussed in the 5G NR standard, the system will benefit from a flexible measurement period (SS burst period). From the above discussion, it is clear that the tracking accuracy can be further improved, if the measurement update \( T_m \) becomes smaller, as the \( q_t \) in the Kalman Filter captures the mean rotation generated by the translation in the previous measurement period. The inertia of typical motions guarantees the validity of this measurement. However, the self-correlation decreases with increasing average time. For indoor mmWave communications, an SS burst period less than 100ms is suggested for narrow beam tracking given the above experiment results.

**VI. Overhead Evaluation**

The tracking accuracy is a direct way to understand the limitation of the beam tracking process. The overhead for beam tracking also depends on the system configuration and hardware setup. Therefore, in this section we study the overhead of beam tracking in a numerical approach.

**A. Simulation Setup**

We simulate the tracking overhead in the 5G NR system. Within one cell as shown in Fig. ??, the initial positions of multiple users are uniformly distributed around the BS, within a range between 50 – 100 meters. Then their trajectories are characterized by the optical tracking system. The antenna systems on both sides are considered to generate simple cone beams with flat antenna gains \( G_t \) and \( G_r \), respectively. The beam width follows an asymmetric design, where the BS has more system resource to generate narrower beams. On the other end, the UEs are equipped with wider beam width given the limited number of antennas.
Fig. 15: Tyres dataset—comparison of mean angle mismatch and 95% confidence interval for various compensation strategies

As we have introduced in Section II, each IA starts with an SS burst. Although one SS burst may not cover all the directions in one period, for simplicity we assume that one SS burst provides sufficient training for all directions without loss of generality. Essentially speaking, a multi SS-burst that cover all directions is equivalent to one single omnidirectional SS burst period. With this procedure, we set the SS burst time $T_{IA}$ as 160ms to match the maximum period in 5G NR. The trained beam direction identified after the SS burst is considered as the optimal choice. The UE will correct its beam choice until the angle mismatch falls to the half beam width. This mismatch will trigger the UE to request an aperiodic CSI-RS signal to explicitly refine the beam direction.

B. Overhead Reduction with Motions

We choose to evaluate the overhead of beam tracking when the UE and BS have 10° and 5° beam widths, respectively. To compare the beam tracking overhead across over all types of motions, we normalize the overhead by the greatest one due to the significant distinction with respect to the motions. The results are shown in Fig. 16, where the greatest overhead is
achieved in the indoor swinging motion and outdoor running hand. All the intense motions require considerately more tracking overhead in the simulation, up to 10 times higher.

As for the tracking overhead reduction, all the tracking schemes show dramatic reductions to the overhead, where our proposed method (KF+gyro) achieves the optimal performance, which shows uniform advantages over all motions and scenarios. For outdoor scenes, most motions require no refinement with the sensor-aided tracking schemes. In contrast to this observation, the indoor scenario still needs a few corrections after the sensor-aided tracking. However, our method is even able to reduce most of the overhead by at least 96% compared with uncompensated cases. This result strongly supports the efficiency of the sensor-based beam tracking for mmWave communication systems.

![Graphs showing beam tracking overhead comparison](image)

Fig. 16: Beam tracking overhead comparison: BS beamwidth: $5^\circ$ UE beamwidth: $10^\circ$ SS-Period: 160ms. normalized by the highest overhead of all motions: AR, phoning, running hand, running pocket, swinging, texting (from left to right).

C. Discussion on Beam Width

Besides the motion, the overhead of beam adjustment also relies on the choice of beam width. The analysis of the impact of beam width is given below with respect to various UE beam
In Fig. 17, narrow beam communications in both outdoor and indoor environments are more vulnerable to the beam mismatch. Thus a high overhead is expected. Until the beam is wider than 40°, the tracking overhead remains high for the scheme without sensor compensation. A wider beam width implies that at least a 6dBi loss be expected to form the antenna gain. For the sensor-aided beam tracking, the overhead reduces to almost zero when the beam width is above 20°. In conclusion, significant improvements to the tracking overhead can be observed. Because the beam width of the mobile UE is larger than 10° in practical design, it is possible to save a lot of system resource and maintain a consistent link with the sensor-aided beam tracking.

VII. CONCLUSIONS

In this paper, we have thoroughly examined the sensor-aided beam tracking for various types of motion in two scenarios. From the observation and analysis of two datasets, we have verified that the rotation of UE is responsible for most of the overhead in the beam tracking procedure. In most cases, the beam mismatch can be well controlled by a rotation-only sensor-aided beam tracking scheme. The only exception is the compensation of translation. We have proposed an extended KF based algorithm to estimate the approximate rotation caused by the translation of the UE’s centroid. The experiment has shown that our approach efficiently reduces the requirement
of beam tracking. Finally, the simulation of system overhead has demonstrated that our proposed method almost eliminates the overhead in the outdoor scenario, while at most a 4% tracking overhead remains for the indoor scenarios.

REFERENCES


