Abstract—In this paper, we present a novel mobile user tracking (UT) scheme for codebook-based intelligent reflecting surface (IRS)-aided millimeter wave (mmWave) systems. The proposed UT scheme exploits the temporal correlation of the direction from the IRS to the mobile user for selecting IRS phase shifts that provide reflection towards the user. To this end, the user’s direction is periodically estimated based on a generalized likelihood ratio test (GLRT) and the user’s movement trajectory is extrapolated from several past direction estimates. The efficiency of the proposed UT scheme is evaluated in terms of the average effective rate, which accounts for both the required signaling overhead and the achievable signal-to-noise ratio (SNR). Based on simulations, the proposed UT scheme is compared to two baseline schemes employing a full codebook search and optimization of the phase shifts of the IRS unit cells based on full CSI, respectively. Our results reveal that the proposed UT scheme outperforms the full codebook search and the full CSI baselines at medium-to-high SNRs.

Notations: Lower case and upper case bold letters denote vectors and matrices, respectively. The transpose and conjugate transpose of matrix A are denoted by $A^T$ and $A^H$, respectively. $I_N$ is the identity matrix of size $N$. The $i$-th element of vector $a$ is denoted by $[a]_i$, and the element in the $i$-th row and $j$-th column of matrix A is denoted by $[A]_{i,j}$. A complex normal distributed vector with mean vector $x$ and covariance matrix $A$ is represented by $CN(x,A)$. Furthermore, the complex conjugate, absolute, and expected values of a scalar $x$ are denoted by $x^*$, $|x|$, and $E\{x\}$, respectively. The $l^p$-norm is denoted by $\|x\|_p$. The cardinality of set $M$ is denoted by $|M|$. The sets $\mathbb{N}$ and $\mathbb{C}$ denote natural and complex numbers, respectively. Finally, the big-O notation is denoted by $O(\cdot)$.

I. INTRODUCTION

In the past years, millimeter wave (mmWave) systems have been thoroughly analyzed, as they exploit previously unused spectrum and enable high data rates in wireless communication systems [1]. For mmWave frequencies, high path loss leads to few scatterers and a channel that is sparse in the angular domain, i.e., the received signal arrives from only few separable directions [1]. Intelligent reflecting surfaces (IRSs) have been introduced to improve the channel gain for scenarios where the dominant line-of-sight (LoS) path is blocked. By configuring the phase shifts of its unit cells properly, the IRS can create a programmable propagation path [2]. Configuring the IRS requires channel state information (CSI), which is difficult to obtain in practice due to the typically large number of unit cells and the lack of sensing capabilities at the IRS. As an alternative, resource-intensive channel estimation may be circumvented by configuring the IRS based on predefined codewords from a phase shift codebook [3].

For systems without IRS, the problem of direction estimation has been discussed extensively in the literature, where sensing at the base station (BS) antenna array is usually employed to infer information about the angle of departure (AoD) (see, e.g., [4]). However, these user tracking (UT) schemes can not be employed in passive IRS-assisted systems. A multiple IRS-assisted UT scheme for linear movement has been proposed in [5]. However, to the best of the authors’ knowledge, codebook-based IRS-assisted UT schemes for general non-linear user movement have not been reported, so far.

In this paper, we propose a novel UT scheme, for IRS-assisted wireless systems, that selects codewords from a predefined codebook to strengthen the LoS link from the IRS to the user. For user direction estimation, a generalized likelihood ratio test (GLRT) framework is proposed, and to minimize the signaling overhead, several past direction estimates are used to predict the user’s future directions. We analyze the resulting effective rate of the system, which accounts for the tradeoff between signaling overhead and achievable signal-to-noise ratio (SNR). Based on simulations, the proposed UT scheme is compared to two baseline schemes employing a full codebook search and optimization of the phase shifts of the IRS unit cells based on full CSI, respectively. Our results reveal that the proposed UT scheme outperforms the full codebook search and the full CSI baselines at medium-to-high SNRs.

II. SYSTEM MODEL

The considered system is illustrated in Fig. 1. The coordinate system is defined by $[x,y,z]$. We consider a downlink system with one multi-antenna BS equipped with $N_{BS}=N_{BS,x}\times N_{BS,y}$ antennas arranged as an uniform planar array (UPA) in the $x$-$z$ plane, and one single-antenna user. Furthermore, an IRS consisting of $Q=Q_y\times Q_z$ unit cells lies in the $y$-$z$ plane, with unit cell area $A_{UC}=d_y\times d_z$. For an array lying in the $u_1$-$u_2$ plane, vector $\mathbf{u}=[u_1,u_2,u_3]^T$ is parameterized by $\Psi(\mathbf{u})=[\theta,\phi]^T$ with $\theta=\arctan(u_1/u_3)$ and $\phi=\arctan(u_2/u_3)$, for $u_3>0$. The direct link between the BS and the user is assumed to be completely blocked. The positions of the centers of the antenna arrays at the BS and IRS are denoted as $\mathbf{p}_{BS}$ and $\mathbf{p}_{IRS}$, respectively. Throughout this paper, we assume that the positions of the BS and IRS are known, while the position of the user is generally unknown.

A. Codebook-Based Channel Model

In this paper, we use a geometry-based transmission model that is defined by a limited number of propagation paths [3]. The received signal at the user is given by [3]

$$y(m,t) = a_{UE}\Sigma_{UE}G(m)\Sigma_{BS}D_{BS}^H(t)s(t) + n(t),$$

We assume that the BS UPA and the IRS are located in the $x$-$z$ and $y$-$z$ planes, respectively. Adopting a more involved notation, the proposed UT scheme can be adapted to general positions and orientations.
Fig. 1. The considered system consists of a BS, an IRS, and a user that moves within an obstructed area. The direct link between BS and user is blocked.

where $\mathbf{a}_{\text{UE}} = [a_1, ..., a_{L_{\text{UE}}}] \in \mathbb{C}^{L_{\text{UE}}}$ contains unit norm scalars modeling the phases of the different reception paths at the user, $\mathbf{D}_{\text{BS}} = [\mathbf{d}_1, ..., \mathbf{d}_{L_{\text{BS}}}] \in \mathbb{C}^{N_{\text{BS}} \times L_{\text{BS}}}$ contains the steering vectors for the AoDs at the BS, $\mathbf{z}_{\text{UE}} \in \mathbb{C}^{L_{\text{UE}} \times L_{\text{UE}}}$ and $\mathbf{z}_{\text{BS}} \in \mathbb{C}^{L_{\text{BS}} \times L_{\text{BS}}}$ are diagonal matrices containing the channel gains of the respective paths, and matrix $\mathbf{G}(m) \in \mathbb{C}^{L_{\text{BS}} \times L_{\text{BS}}}$ contains the IRS response for all incoming to all outgoing directions for codeword $m$ from set $\mathcal{M}$, where $L_{\text{BS}}$ and $L_{\text{UE}}$ denote the numbers of paths in the BS-to-IRS and IRS-to-user channels, respectively. By convention, we assume that $a_1$ and $d_1$ correspond to their respective LoS paths. We assume Rician fading, and the ratio of the power of the LoS path to that of all other paths is denoted as $K = \frac{\|\mathbf{z}_{\text{BS}}\|^2}{\sum_{i=2}^{L_{\text{BS}}} \|\mathbf{z}_{\text{BS}}\|^2}$, $i \in \{\text{BS}, \text{UE}\}$. Furthermore, $y(m, t), f(t) \in \mathbb{C}^{N_{\text{BS}}}, s(t) \in \mathbb{C}$, and $n(t) \sim CN(\mathbf{0}, \sigma^2)$ represents the received signal for codeword $m$ at the user, the beamformer at the BS, the transmit symbol, and additive white Gaussian noise with power $\sigma^2$, respectively. For simplicity, the transmit power $P_{\text{TX}} = \mathcal{E}(|s(t)|^2)$ is assumed to be identical for pilot and data symbols. Furthermore, the transmit signal vector is set to beamform towards the IRS, i.e., $f(t) = f = d_1$, since the position of BS and IRS are known. Matrix entry $[\mathbf{G}(m)]_{ij}$ is the IRS response function $g_m(\mathbf{g}_{\text{BS}}(\mathbf{u}_{\text{UE}}))$ of codeword $m$ for the $i$-th angle of arrival (AoA) $\Psi_{\text{BS}}$ and the $j$-th AoD $\Psi_{\text{UE}}$. The IRS response function is given by [2]

$$g_m(\mathbf{g}_{\text{BS}}(\mathbf{u}_{\text{UE}})) = \sum_{q_y=0}^{Q_y-1} \sum_{q_z=0}^{Q_z-1} \left[ d_y A_y(\mathbf{g}_{\text{BS}}(\mathbf{u}_{\text{UE}})q_y + d_z A_z(\mathbf{g}_{\text{BS}}(\mathbf{u}_{\text{UE}})q_z), \omega_{q_y,q_z}(m) \right],$$

where $\lambda$ is the wavelength, $\omega_{q_y,q_z}(m)$ is the phase shift of the $(q_y,q_z)$-th unit cell, and $\tilde{g} = \frac{4\pi A_{\text{UC}}}{\lambda^2}$.

Furthermore, we define $A_y(\mathbf{g}_{\text{BS}}(\mathbf{u}_{\text{UE}})) = A_y(\mathbf{g}_{\text{BS}}) + A_y(\mathbf{u}_{\text{UE}})$ and $A_z(\mathbf{g}_{\text{BS}}(\mathbf{u}_{\text{UE}})) = A_z(\mathbf{g}_{\text{BS}}) + A_z(\mathbf{u}_{\text{UE}})$ with $A_y(\mathbf{g}) = \sin(\alpha) \cos(\epsilon)$ and $A_z(\mathbf{u}_{\text{UE}}) = \sin(\alpha) \sin(\epsilon)$, where $\alpha = \arctan(\sqrt{\tan^2(\phi) + \tan^2(\theta)})$ and $\epsilon = \arctan(\tan(\theta)/\tan(\phi)) + \frac{\pi}{2} (1 - \sin(\tan(\phi))$ [6].

While the proposed UT scheme is applicable for general IRS phase-shift codebooks, for concreteness, we adopt the so-called quadratic codebook, which allows a flexible selection of the codebook size and beamwidth [6]. This codebook parameterizes the codewords $m$ by tuples $(m_y, m_z)$, with $m_y \in \{0, ..., M_y - 1\}$, $m_z \in \{0, ..., M_z - 1\}$, and $M = M_Y M_Z$. In particular, the phase shift of unit cell $(q_y, q_z)$ for codeword $(m_y, m_z)$ is given as [6]

$$\omega_{q_y,q_z}(m_y,m_z) = -\pi \left[ \frac{w \Delta \beta_{y,m_y} q_y^2 + \beta_{y,m_y} q_y}{2Q_y} \right] - \pi \left[ \frac{w \Delta \beta_{z,m_z} q_z^2 + \beta_{z,m_z} q_z}{2Q_z} \right].$$

where $\beta_{i,m_i+1} = \beta_{i,m_i} + \Delta \beta_i, \Delta \beta_i = \frac{\pi}{2 \lambda}, \beta_{i,0} = -1$, for $i \in \{y, z\}$, and parameter $w \geq 0$ controls the beamwidth. In this paper, we employ $w = 2$, which generates partially overlapping IRS beams. Furthermore, we define the main lobe direction of the beam generated by codeword $m$, $\Psi_{\text{IRS}}(m) = (\theta_{\text{IRS}}(m), \phi_{\text{IRS}}(m))$, as the direction in which the highest reflection gain is achieved.

B. Transmission Block Structure

Before tracking the user, an initial connection from the BS to the user via the IRS has to be established, i.e. the codeword $m(0)$ providing the largest reflection gain for the initial user position has to be found. In this paper, we focus on the tracking phase, since the establishment of the initial connection has been studied extensively in the literature, e.g., [7]. The available time is divided into transmission blocks of equal length that start immediately after the initial connection, enumerated by $k \in \mathbb{N}$. Each transmission block starts with an IRS direction estimation (IDE) frame, which is followed by $\eta \in \mathbb{N}$ alternating channel estimation (CE) and data transmission (D) frames, see Fig. 2. The durations of the IDE, CE, and D frames are denoted as $T_{\text{IDE}}, T_{\text{CE}}$, and $T_{\text{D}}$, respectively. The data is transmitted during the D frames and the CE frames are used to estimate the end-to-end channel from the BS to the user including the impact of the IRS. The start time of transmission block $k$ is denoted by $\tau_k$, and the transmission block duration is $T = T_{\text{IDE}} + \eta(T_{\text{CE}} + T_{\text{D}})$. During the CE and D frames, the IRS-to-user direction is predicted based on previous direction estimates in the IDE frames, which allows selecting an appropriate codeword from the codebook. For a mobile user, small-scale fading causes rapid changes to the channel parameters, whereas the direction changes only slowly. Therefore, the proposed UT scheme operates on two time scales, where CE has to be performed in short intervals as $T_{\text{CE}} + T_{\text{D}}$ can not exceed the channel coherence time, but IDE can be performed infrequently [7].

III. CODEBOOK-BASED TRACKING SCHEME

In this section, we first propose a method to estimate the the user’s direction. Subsequently, we extrapolate the movement trajectory for the entire following transmission block.
A. Direction Estimation

We assume that the IRS is fully passive and cannot perform sensing. Therefore, we estimate the direction from the IRS to the user, \( \Psi_{\text{UE}} \), at the user and then feed it back to the BS via a control channel. To this end, the IRS cycles through several candidate codewords, while the BS sends a pilot sequence of length \( N_{\text{IDE}} \) for each candidate codeword. The candidate codewords \( m \) are chosen such that their main lobe directions, \( \Psi_{\text{IRS}}(m_y,m_z) \), are adjacent to the main lobe direction, \( \Psi_{\text{IR}}(m_y,m_z) \), of the currently employed codeword \( m \), and are defined by the set \( (m_y,m_z) \in \mathcal{M}_{\text{IDE}} \) where \( \| (m_y,m_z) - (m_y,m_z) \|_{\infty} \leq \gamma \). Here, \( \gamma \in \mathbb{N} \) is the maximum difference between the codeword indices. For simplicity, we assume that the pilot sequence is identical for all codewords and is denoted by \( s \in \mathbb{C}^{N_{\text{IDE}}} \). We collect all measurements obtained for candidate codeword \( m \) in vector \( y_{m} \in \mathbb{C}^{N_{\text{IDE}}} \), such that \( [y_{m}]_{i} = y_{m,IDE} + (j - 1)T_{s} \), \( \forall m \in \mathcal{M}_{\text{IDE}} \), where \( T_{s} \) denotes the symbol duration, \( t_{m}^{\text{IDE}} \) denotes the time when the IRS is reconfigured with codeword \( m \). For direction estimation, we simplify the system model in (1), since the LoS path is dominant at mmWave frequencies [1] and the IRS reflection codebook creates a narrow beam. Therefore, the received signal is approximated as follows\(^2\)

\[
y(m,t) \approx g_{m}(\Psi_{\text{BS}},\Psi_{\text{UE}})h_{s}(t) + n(t),
\]

where \( h = a_{1}[\Sigma_{\text{UE}}]_{1,1}[\Sigma_{\text{BS}}]_{1,1}d_{\text{f}}^{1/2}f \) models the joint impact of the beamforming at the BS and the LoS channel. To estimate the direction of the user in the IDE frame of transmission block \( k \), we adopt the GLRT-approach, which compares the likelihood of a set of hypotheses \( \Psi_{\text{UE}} \in \mathcal{H} \), involving the unknown effective channel gain \( h \) [8], i.e.,

\[
\hat{\Psi}_{\text{UE}}(k) = \arg\max_{\Psi_{\text{UE}} \in \mathcal{H}} \max_{h} \prod_{m \in \mathcal{M}_{\text{IDE}}} f(y_{m} | \Psi_{\text{UE}}, h, s),
\]

where \( f(y_{m} | \Psi_{\text{UE}}, h, s) \) is the conditional probability density function of \( y_{m} \). Here, \( f(y_{m} | \Psi_{\text{UE}}, h, s) \) is a complex Gaussian distributed with mean vector \( g_{m}(\Psi_{\text{BS}},\Psi_{\text{UE}})h_{s} \) and covariance matrix \( \sigma^{2}I_{\text{IDE}} \), and we assume that \( h \) is constant because the IDE frame is shorter than the channel coherence time. The inner maximization in (5) over the effecting channel, \( h \), that maximizes the likelihood of the observation, given a hypothesis \( \Psi_{\text{UE}} \), can be obtained by setting the derivative of the objective function of (5) with respect to \( h \) to zero [8]. This yields

\[
\hat{h}(\Psi_{\text{UE}}) = \frac{\sum_{m \in \mathcal{M}_{\text{IDE}}} g_{m}(\Psi_{\text{BS}},\Psi_{\text{UE}})h_{s}y_{m}}{\sum_{m \in \mathcal{M}_{\text{IDE}}} N_{\text{IDE}}P_{\text{TX}}|g_{m}(\Psi_{\text{BS}},\Psi_{\text{UE}})|^{2}}.
\]

Now, according to the GLRT principle [8], we insert (6) into (5). Thus, (5) can be equivalently reformulated as a non-linear least squares minimization problem:

\[
\hat{\Psi}_{\text{UE}}(k) = \arg\min_{\Psi_{\text{UE}} \in \mathcal{H}} \sum_{m \in \mathcal{M}_{\text{IDE}}} \| y_{m} - \hat{h}(\Psi_{\text{UE}})g_{m}(\Psi_{\text{BS}},\Psi_{\text{UE}}) \|_{2}^{2}.
\]

Since we cannot solve (7) in closed form, we evaluate (7) for the set of hypotheses \( \mathcal{H} = \{ (\theta_{1}, \phi_{1}), \ldots, (\theta_{I}, \phi_{I}) \} \), \( I \in \mathbb{N} \). For realistic human movement, the user’s position is close to its last known position if the transmission block length is short, such that the set of hypotheses \( \mathcal{H} \) is limited by the directions covered by the candidate codewords in \( \mathcal{M}_{\text{IDE}} \), where codeword \( m \) covers all directions \( \Psi_{\text{IRS}} \) with \( m = \arg\min_{m \in \mathcal{M}} \| \Psi_{\text{IRS}}(m) - \Psi_{\text{IRS}} \|_{2}^{2} \). Therefore, set \( \mathcal{H} \) is defined by \( \hat{\theta}_{n} = \hat{\theta}_{\text{IRS}}(\tilde{m}) + (n \frac{2\gamma + 1}{M_{\text{y}}} - 0.5 - \gamma) \frac{180^\circ}{M_{\text{y}}} \) and \( \hat{\phi}_{n} = \phi_{\text{IRS}}(\tilde{m}) + (n \frac{2\gamma + 1}{M_{\text{y}}} - 0.5 - \gamma) \frac{180^\circ}{M_{\text{y}}} \), \( n \in \{0, \ldots, H - 1\} \).

B. Extrapolation of the Trajectory

To reconfigure the employed IRS codeword after the IDE frame during the transmission block, we exploit the strong correlation between the past direction estimates and the future movement of the user. Thus, we extrapolate the user’s trajectory from past direction estimates at the BS. To this end, we assume that the user’s movement direction is a smooth function of time over long periods, i.e., at least for several seconds. This property has been exploited in [9] and [10] to predict the future position of a user in codebook-based UT schemes for wireless systems without IRS, by linear extension of three past position measurements. We extend this concept to IRS-assisted systems by fitting an arbitrary number of past estimates to an \( n \)-th order polynomial:

\[
\hat{\Psi}_{\text{UE}}(t) = \sum_{i=0}^{n} c_{i}t^{i},
\]

where \( \hat{\Psi}_{\text{UE}}(t) = [\hat{\theta}_{\text{UE}}(t), \hat{\phi}_{\text{UE}}(t)]^{T} \) is the predicted direction at time \( t \), and \( c_{i} = [c_{i,\theta}, c_{i,\phi}]^{T} \), \( \forall i \), are the weights of the polynomial. We adopt the direction estimates obtained in the last \( S \) IDE frames, c.f. (7), for curve fitting\(^3\) and minimize the mean square error (MSE) between the trajectory and the direction estimates:

\[
\min_{c_{0}, \ldots, c_{n}} \frac{1}{S} \sum_{k=k'-s+1}^{k'} \left\| \hat{\Psi}_{\text{UE}}(t_{k}^{\text{TH}}) - \hat{\Psi}_{\text{UE}}(k) \right\|_{2}^{2},
\]

where the current IDE frame is denoted by \( k' \). Equation (9) can be solved analytically by setting the derivatives of the polynomial weights, \( c_{i} \), to zero. We omit the resulting expression due to space constraints. The polynomial weights are computed in every IDE frame after direction estimation before the start of the following CE frame. Thus, at the beginning of each CE frame, i.e., at times \( t' = t_{k}^{\text{TH}} + T_{\text{IDE}} + i_{\text{CE}}(T_{\text{CE}} + T_{D}) \), \( i_{\text{CE}} = 0, \ldots, \eta - 1 \), the BS uses the extrapolated trajectory to determine the codeword, whose main lobe direction is closest to \( \hat{\Psi}_{\text{UE}}(t) \), as follows

\[
\tilde{m}(t') = \arg\min_{m \in \mathcal{M}} \left\| \hat{\Psi}_{\text{UE}}(t') - \Psi_{\text{IRS}}(m) \right\|_{2}^{2}.
\]

The proposed UT scheme is summarized in Algorithm 1.

C. Remarks on the Overhead

The main advantage of the proposed UT scheme is its low overhead, which is quantified in the following. As explained in Section II-B, in each transmission block, one IDE frame and \( \eta \) CE frames are needed in addition to the \( \eta \) D frames. The percentage of time needed for those frames, i.e., the resulting

\(^2\)We note that the impact of scattering in the channel is included in our simulation results shown in Section IV.

\(^3\)During the first few transmission blocks, the number of past direction estimates and the order of the polynomial have to be reduced.
We consider two baseline schemes where \( N_{\text{ref}} \) and \( N_{\text{CE}} \) are the number of pilot symbols for CE. For recovery, neglecting noise, \( N_{\text{CE}} \) needs to be at least as large as the number of channel coefficients to be estimated. For the proposed UT scheme, \( h \) is a scalar and thus, the number of pilot symbols for CE does not scale with the IRS size, e.g., \( N_{\text{CE}} \sim O(1) \). In contrast to our approach, most existing schemes in the literature require full CSI, comprising the individual channels of each IRS unit cell, and design the IRS phase shifts for one subsequent D frame. This yields a signaling overhead of \( \Gamma = \frac{T_{\text{BS}}}{T_{\text{CE}} + T_{\text{CE}}} \), with \( T_{\text{CE}} = N_{\text{CE}} T_{\text{S}} \), where \( N_{\text{CE}} \) and \( T_{\text{S}} \) denote the corresponding pilot sequence length and the duration of the D frame, respectively. To estimate the channel efficiently, compressed sensing (CS) schemes have been proposed that exploit the sparsity of the mmWave channel. In this case, the required number of pilot symbols scales with \( N_{\text{CE}} \sim O(\sqrt{N_{\text{CE}}}) \) [11].

### IV. Performance Evaluation

For the following evaluation, we use a movement model similar to the one in [12], where the user moves with constant speed \( v \) inside a circle of radius \( r \). The movement involves three stages. First, the user enters the circle from a random angle and moves towards the center. When reaching a distance of \( r_c \) to the center, the user follows a circular trajectory around the center in counter-clockwise direction. Finally, at a random angle, the user moves straight away from the center and leaves the circle. The simulation parameters are collected in Table I.

| \( \gamma \) | \( n_{\gamma} \) | \( \Delta f \) | \( T_{\text{S}} \) |
|------------|-------------|-------------|-------------|
| 0.0, 0.1, 0.2 m | 0.0, 0.1, 0.2 | 0.0, 0.1, 0.2 | 0.0, 0.1, 0.2 |
| \( Q_{\text{CE}} \) | \( Q_{\text{ref}} \) | \( N_{\text{ref}} \) | \( N_{\text{CE}} \) |
| 100, 100 | 100, 100 | 100, 100 | 100, 100 |
| \( T_{\text{S}} \) | \( T_{\text{CE}} \) | \( T_{\text{ref}} \) | \( T_{\text{ref}} \) |
| 1.29 ms | 1.29 ms | 1.29 ms | 1.29 ms |
| \( r_c \) | \( r_c \) | \( r_c \) | \( r_c \) |
| 5 km/h | 5 km/h | 5 km/h | 5 km/h |
| \( T_{\text{BS}} \) | \( T_{\text{UE}} \) | \( T_{\text{CE}} \) | \( T_{\text{CE}} \) |
| 4, 4 | 4, 4 | 4, 4 | 4, 4 |
| \( K \) | \( K \) | \( K \) | \( K \) |

We cannot compare with the UT scheme in [5], since it assumes linear movement and employs an algorithm that is not computationally feasible for large IRS.

The effective rate as a function of the BS transmit power \( P_{\text{TX}} \) is shown in Fig. 3. The results show that our proposed UT scheme outperforms FS for medium-to-high transmit powers. In this range, the IRS reflection gain achieved by both schemes is similar, since both schemes employ the same codebook and erroneous codebook selection rarely occurs, but the overhead of FS is larger leading to a lower effective rate. In the low power regime, inaccurate direction estimation may cause the proposed UT scheme to select codewords that provide a suboptimal reflection gain. This has a less severe impact on FS as it cycles through the entire codebook in each IDE frame. Furthermore, Fig. 3 shows that for FS, the higher reflection gain enabled by a larger codebook (\( M=6400 \)) does not compensate for the resulting higher overhead, such that a smaller codebook (\( M=4900 \)) achieves a higher effective rate.

The full optimization of the IRS phase shifts constitutes an upper bound for the achievable reflection gain of the IRS, but the required overhead is high. Thus, the significantly lower signaling overhead of the proposed UT scheme leads to a higher effective rate in medium-to-high transmit power regime, since the signaling overhead affects the rate linearly, while the SNR affects the rate only logarithmically.

### V. Conclusion

In this paper, a novel UT scheme for codebook-based IRS-assisted systems was introduced. The proposed UT scheme exploits the high temporal correlation of a moving user’s direction, by regularly estimating the user’s direction based on a GLRT approach and subsequently extrapolating the user’s movement trajectory. Our simulation results have revealed that for sufficiently high SNR the proposed scheme achieves a significantly higher effective rate than two baseline schemes from the literature.
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