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Limited Channel Feedback Scheme for Reconfigurable Intelligent Surface Assisted MU-MIMO Wireless Communication Systems

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ABSTRACT This paper proposes the efficient downlink channel state information (CSI) feedback scheme for reconfigurable intelligent surface (RIS) assisted multi-user multi-input multi-output (MU-MIMO) wireless communication systems. RIS is the state-of-the-art technology that is extensively researched as the solution to solve the problems derived from the sparse propagation environment of the millimeter wave (mmWave) communication systems. For optimal performance, the reliable downlink CSI for designing the phase shift value of the RIS reflective elements and the precoder for beamforming is necessary at the base station (BS). However, in the practical environment, the channel feedback problem occurs due to the large number of reflective elements constituting the RIS. In this paper, to alleviate this problem, compressive sensing (CS) based channel feedback scheme is proposed. By utilizing sparse nature of mmWave propagation environment, the downlink CSI is compressed with the small number of channel vector and the corresponding index is transferred to the BS. Then, the BS acquires downlink CSI by employing the recovery algorithm of CS. The simulation results show that the proposed channel feedback scheme achieves the improved performance compared to conventional scheme in multi-user and limited scattering environment.

INDEX TERMS MU-MIMO, channel feedback, reconfigurable intelligent surface, compressive sensing, mmWave.

I. INTRODUCTION

In wireless communication systems, higher frequency bands are allocated and operated in order to provide higher peak data rates and system capacity. In the case of the fifth-generation New Radio (5G NR), mmWave bands of 24 GHz$\sim$50 GHz are allocated. This technology tendency can be continued in beyond the fifth-generation (B5G) or sixth-generation (6G) wireless communication systems, and it is expected that the sub-THz bands of 114GHz$\sim$300GHz will be utilized [1]. Reconfigurable intelligent surface (RIS) is one of the new promising technologies for future B5G or 6G wireless communication systems. RIS is a planar surface with several passive reflective elements which is deployed in the interior walls of the indoor environment, the exterior walls of buildings or glasses of windows, and can independently change the phase of the colliding electromagnetic waves [2]. The RIS has advantage that it is controllable through the controller in real-time [3]. This can be interpreted as having a degree of freedom of a wireless channel in the existing wireless communication systems. In addition, RIS assisted communication systems achieve enhanced spectral efficiency (SE) and energy efficiency (EE) with a low price and power consumption by employing the large-scale passive reflective elements [4], [5].

However, since the mmWave communication systems utilize a high frequency band, signal attenuation and propagation distance attenuation occur in multipath. In this

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environment, wireless channels present sparsity with the small number of dominant paths. Also, in the angular domain, the sparsity is observed since the signals are propagated in similar paths [6]. Therefore, sufficient performance of the system can be limited. To compensate for these disadvantages, a beamforming that guarantees the stable signal transmission is essential. For beamforming in mmWave communication, the BS requires knowledge of wireless channel condition referred to as channel state information at the transmitter (CSIT). However, when CSI at the BS is not reliable, performance improvement of the system through transmit beamforming is limited. Therefore, to realize sufficient beamforming performance, reliable channel estimation and feedback scheme are required. In time division duplex (TDD) systems that the channel reciprocity is considered, the BS can obtain the downlink CSI directly by uplink channel estimation. However, in practical TDD systems, the channel reciprocity is not always fully satisfied because of the constraints of the power consumption and the hardware complexity [7]. In this case, the TDD systems also require feedback of channel information for CSIT. In frequency division duplex (FDD) systems which the channel reciprocity no longer holds, user equipment (UE) requires the feedback of downlink CSI through the uplink channel. The principal hurdle in FDD massive MIMO systems is the feedback overhead that increases proportionally to the number of antennas. Therefore, the reduction of the channel feedback overhead is key challenge in mmWave communication systems.

A. RELATED WORKS

The channel feedback scheme has been already investigated in wireless communication systems. First, the UE obtains downlink CSI by exploiting downlink channel estimation. Then, to reduce the channel feedback overhead, the codebook shared by the BS and the UE is exploited. The channel vector is used to select the most appropriate codeword among the codewords constituting the codebook, and the index of the selected codeword is delivered to the BS. The BS reconstructs downlink CSI by exploiting the received index and pre-shared codebook [8], [9].

In [10], the RVQ codebook based limited channel feedback scheme was proposed for MU-MIMO systems. The UE quantizes downlink CSI into RVQ codebook. Each codeword is unit norm vector, which is independently and randomly generated from the isotropic distribution. In massive MIMO system, a large number of transmit antennas are deployed to obtain a multiplexing gain, and the feedback overhead increases in proportion to the number of transmit antennas. Accordingly, the size of codebook and computational complexity to acquire reliable downlink CSI exponentially increase. To reduce computational complexity, efficient channel feedback scheme in mmWave multi-user hybrid beamforming systems was proposed in [11]. By utilizing the sparse nature of the mmWave channel, the beamsteering codebook adopts the analog beamforming vectors. It was shown that the proposed beam steering codebook with relatively small size achieves better performance compared to the RVQ codebook.

Another channel feedback schemes based on compressive sensing (CS) to further reduce the feedback overhead were proposed in [12], [13]. These papers considered the highly correlated channel in spatial domain. In this environment, the CSI can be represented in sparse form in the spatial domain. Then, through the random projections, it facilitates CS to efficiently compress sparse information. Consequently, the compressed CSI is transferred to BS with a low overhead and the reliable downlink CSI is obtained at the BS by employing the signal recovery algorithm of CS. Recently, to solve problem with high computational complexity for high feedback accuracy, deep learning (DL) based channel feedback schemes were proposed in [14]–[16]. In [15], the CNN-based CSI compression and reconstruction structure was proposed. By utilizing long-short term memory (LSTM) layers, the CNN framework learned with time correlation of channels. The proposed algorithms showed that improved normalized mean square error (NMSE) performance compared to conventional CS feedback scheme with least absolute shrinkage and selection operator (LASSO) l_1-solver, and neural networks-based channel feedback schemes by utilizing is CsiNet and RecCsiNet. [14] focused on the FDD massive MIMO systems with high spatial correlation was considered and the feedback scheme of two-stage convolutional neural network (CNN) architectures with bidirectional LSTM (Bi-LSTM) and bidirectional convolutional LSTM (Bi-ConvLSTM) was proposed. The proposed scheme achieves the enhanced BER and system capacity performance than the conventional Karhunen-Loève transform (KLT) basis and discrete cosine transform (DCT) basis based CS feedback schemes, and principal component analysis (PCA) based compression schemes. In multi-user scenario, a novel deep neural network (DNN) approach in FDD massive MIMO systems was proposed in [16]. To jointly design the CSI feedback and precoding, two-step training procedure with DNN architectures is implemented. It was shown that the performance of proposed DNN based scheme outperforms the conventional limited channel feedback scheme with zero-forcing (ZF) precoder, and has a slightly loss than maximal ratio transmission (MRT) precoder.

In contrast to above papers, because of a large number of reflective elements, the downlink CSI requiring feedback to BS increases in the RIS assisted communication systems. In the case of the massive MIMO systems with 64 antennas at the BS, the required size of CSI to support a single antenna user is 64×1. However, in the RIS-assisted massive MIMO systems with 256 reflective elements at the RIS, the required size of CSI is 64×256 [17], [18]. To solve this problem with previous schemes, a high feedback overhead and a large size of codebook are required. In [19], the algorithm to reduce channel feedback overhead in RIS-assisted communication systems was proposed. By utilizing angular of arrival (AoA) and angular of departure (AoD) information, the

BS-RIS-UE cascaded channel was compressed to reduce the channel feedback overhead while the spectral efficiency was ensured.

B. CONTRIBUTIONS

Different from the previous works, in this paper, an efficient channel feedback scheme based on CS for the RIS assisted wireless communication systems is proposed. The main contributions of this work are summarized as follows:

- First, a general RIS-assisted multi-user FDD massive MIMO system considers that the propagation path between BS and UE is blocked. The downlink CSI is obtained at the UE through channel estimation. By exploiting the sparse nature of the mmWave propagation environment, the downlink CSI is converted into the angular domain. Due to the limited scattering environment which is an important characteristic of mmWave communication, the converted angular domain channel matrix has limited non-zero column vectors.
- Next, to reduce the feedback overhead, each non-zero column vector is compressed by employing the CS. In this paper, the discrete Fourier transform (DFT) matrix which is a general example of the sparsifying basis is employed. The sparse vector is obtained by multiplying the non-zero vector to the sparse basis. Then, to compress the sparse vector, the measurement matrix is utilized. To reduce channel feedback overhead, the codebook generated by clustering algorithm is adopted to reduce rate loss derived from quantization error.
- Finally, the BS recovers the sparse vector by the orthogonal matching pursuit (OMP) algorithm, which is widely used due to its low computational complexity. Therefore, reliable downlink CSI is acquired at the BS with proposed channel feedback scheme.

C. ORGANIZATION

The rest of the paper is organized as follows. In section II, the system model and the formulation for the RIS assisted communication channel model are presented, and CS algorithm is introduced. In section III, the efficient channel feedback scheme based on CS is proposed. In section IV, the simulation results are provided. Finally, the conclusion is described in section V.

II. PRELIMINARY

A. SYSTEM MODEL

The Fig. 1 shows the RIS assisted multi-user MIMO wireless system. The BS has M uniform linear array (ULA) antennas, the RIS has N uniform planner array (UPA) elements and the U UEs have single-antenna, respectively.

The received signal at the u-th UE ($u = 1, 2, \ldots, U$) is given as follows [5],

$$y_u = \mathbf{h}_{2,u}^H \Phi \mathbf{H}_1 \mathbf{x} + n_u, \tag{1}$$

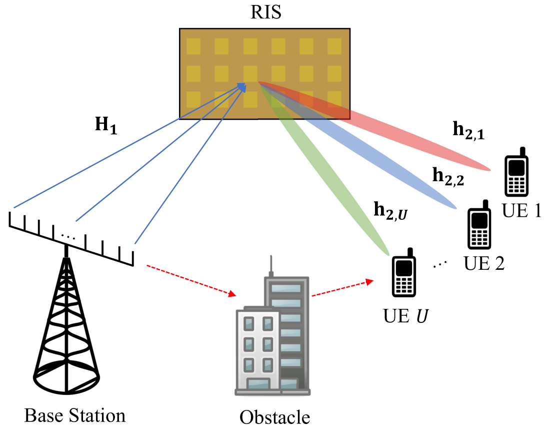

FIGURE 1. The RIS assisted multi-user MIMO system.

where y_u is the received signal at the u-th UE, $\mathbf{x} \in \mathbb{C}^{M\times 1}$ is the precoded transmission signal, $\mathbf{H}_1 \in \mathbb{C}^{N\times M}$ is the channel matrix from the BS to RIS, $\mathbf{h}_{2,u} \in \mathbb{C}^{N\times 1}$ is the channel matrix from the RIS to the u-th UE and $n_u \sim \mathcal{CN}(0,\sigma^2)$ is the additive white Gaussian noise (AWGN) at the u-th UE. $\Phi = \mathrm{diag}(\mathbf{v}) \in \mathbb{C}^{N\times N}$ is a diagonal matrix representing the phase shift values of the reflective elements of the RIS with $\mathbf{v} = [\beta_1 e^{j\phi_1}, \beta_2 e^{j\phi_2}, \ldots, \beta_N e^{j\phi_N}]^T \in \mathbb{C}^{N\times 1}$ where $\beta_n \in [0, 1]$ and $\phi_n \in [0, 2\pi]$ denote the amplitude and the phase coefficient for the n-th reflective element respectively. In this paper, the constant amplitude coefficient ($\beta_n = 1$) is assumed [4], [5], [20].

Next, the entire channel from the BS to the u-th UE through RIS is represented by $\mathbf{h}_{2,u}^H \Phi \mathbf{H}_1 \in \mathbb{C}^{1\times M}$. Specifically, it is worth to note that the matrix $\Phi = \mathrm{diag}(\mathbf{v})$ is diagonal matrix. Then, the aforementioned entire channel matrix $\mathbf{h}_{2,u}^H \Phi \mathbf{H}_1$ can be rewritten as follows,

$$\mathbf{h}_{2,u}^H \Phi \mathbf{H}_1 = \mathbf{h}_{2,u}^H \mathrm{diag}(\mathbf{v}) \mathbf{H}_1 = \mathbf{v}^T \mathrm{diag}(\mathbf{h}_{2,u}^H) \mathbf{H}_1, \tag{2}$$

$$\mathbf{H}_u = \mathrm{diag}(\mathbf{h}_{2,u}^H) \mathbf{H}_1, \tag{3}$$

where $\mathbf{H}_u \in \mathbb{C}^{N\times M}$ is the cascaded channel at the u-th UE and only depends on the downlink CSI [18].

B. CHANNEL MODEL

This paper considers the mmWave propagation characteristics. For the application of this characteristics, three-dimensional (3D) Saleh-Valenzuela channel model is employed since this channel model is statistical channel model in multipath propagation environment. Also, this channel model can reflect the limited propagation environment which is the characteristic of the mmWave communication systems.

The BS-RIS channel $\mathbf{H}_1$ can be expressed as follows,

$$\mathbf{H}_1 = \sqrt{\frac{MN}{P_1}} \sum_{p=1}^{P_1} g_p^1 \mathrm{a}_r(\phi_{r,p}^1, \theta_{r,p}^1) \mathrm{a}_t^H(\phi_{t,p}^1), \tag{4}$$

where $\sqrt{\frac{MN}{P_1}}$ is a normalization factor, P_1 is the number of dominant paths between BS and RIS, $g_p^1 \sim \mathcal{CN}(0,1)$ is the complex gain for the p-th path and $\mathrm{a}_r(\phi_{r,p}^1, \theta_{r,p}^1) \in \mathbb{C}^{N\times 1}$ and $\mathrm{a}_t(\phi_{t,p}^1) \in \mathbb{C}^{M\times 1}$ denote the array response vectors related to RIS and BS. $\phi_{r,i}^1, \theta_{r,i}^1, \phi_{t,i}^1$ are the azimuth and elevation AoA and azimuth AoD respectively. The array response vectors can be expressed as follows [21],

$$\mathbf{a}(\phi, \theta) = \frac{1}{\sqrt{N}}[1, \ldots, e^{j\frac{2\pi}{\lambda}d_r(n_1\cos(\theta)\sin(\phi)+n_2\sin(\theta))}, \ldots, e^{j\frac{2\pi}{\lambda}d_r((N_1-1)\cos(\theta)\sin(\phi)+(N_2-1)\sin(\theta))}]^T, \quad (5)$$

$$\mathbf{a}(\phi) = \frac{1}{\sqrt{M}}[1, \ldots, e^{j\frac{2\pi}{\lambda}d_a(m\sin(\phi))}, \ldots, e^{j\frac{2\pi}{\lambda}d_a((M-1)\sin(\phi))}]^T, \quad (6)$$

where d_r, d_a are the spacing of the RIS elements and the BS antennas respectively and λ is the signal wavelength, $0 \le n_1 < N_1$ and $0 \le n_2 < N_2$ denote horizontal and vertical indices of the RIS element, respectively. Accordingly, the size of the RIS elements is $N = N_1N_2$ and $0 \le m < M$ is the index of the BS antenna.

Then, the channel vector $\mathbf{h}_{2,u}$ between the RIS and the u-th UE can be expressed as follows,

$$\mathbf{h}_{2,u}^H = \sqrt{\frac{M}{P_2}}\sum_{p=1}^{P_2} g_p^2 \mathrm{a}_t^H(\phi_{t,p,u}^2, \theta_{t,p,u}^2), \quad (7)$$

where $\sqrt{\frac{M}{P_2}}$ is a normalization factor, P_2 is the number of dominant paths between the RIS and the u-th UE, $g_p^2 \sim \mathcal{CN}(0,1)$ is the complex gain for the p-th path, $\phi_{t,p,u}^2, \theta_{t,p,u}^2$ are the azimuth and elevation AoD respectively. The array response vector $\mathbf{a}_t(\phi_{t,p,u}^2, \theta_{t,p,u}^2)$ can be expressed similarly through expression (5).

Finally, according to (3), (4) and (7), the cascaded channel matrix $\mathbf{H}_u$ acquired at the u-th UE can be expressed as follows,

$$\mathbf{H}_u = \sqrt{\frac{M^2N}{P_1P_2}}\sum_{p=1}^{P_1}\sum_{q=1}^{P_2} g_p^1 g_{u,q}^2 \times \mathrm{diag}(\mathrm{a}_t^H(\phi_{t,q,u}^2, \theta_{t,q,u}^2))\mathrm{a}_r(\phi_{r,p}^1, \theta_{r,p}^1)\mathrm{a}_t^H(\phi_{t,p}^1). \quad (8)$$

C. COMPRESSIVE SENSING

According to the compressive sensing (CS) theory, a general signal is sparse signal that the most of the values are zero when a signal is transformed into a specific signal space. This sparse signal can perfectly recover the original signal with a small number of linear measurements. The signal vector $\mathbf{x} \in \mathbb{C}^{N\times 1}$ can be sparsified as follows,

$$\mathbf{s} = \mathbf{T}^H\mathbf{x}, \quad (9)$$

where $\mathbf{s} \in \mathbb{C}^{N\times 1}$ is a sparsifed signal vector with a sparsifying basis $\mathbf{T} \in \mathbb{C}^{N\times N}$. The signal vector s has only K non-zero elements which are referred K-sparse, where $K \ll N$. By employing the measurement matrix $\mathbf{A} \in \mathbb{C}^{M\times N}$ which elements of matrix are generated by independent and identically distribution (i.i.d.), the compression of the K-sparse signal vector s is expressed as follows,

$$\begin{aligned} y &= \mathbf{Ax} \\ &= \mathbf{ATs} \\ &= \mathbf{Fs}, \end{aligned} \quad (10)$$

where $M \ll N$, $y \in \mathbb{C}^{M\times 1}$ is measurement vector and $\mathbf{F} \in \mathbb{C}^{M\times N}$ is sensing matrix.

For stable recovery of the sparse vector $\mathbf{s}$ from the measurement vector y, the design of a stable measurement matrix and a signal recovery algorithm need to solve. For stable measurement matrix, the sensing matrix $\mathbf{F}$ needs to satisfy the restricted isometry property (RIP) condition [12], [22]. The design of a signal recovery algorithm needs to solve under-determined system in (10) which the number of equations is less than the number of unknowns. This problem can be solved by l_1-norm minimization problem as follows,

$$\min \|\mathbf{s}\|_{l_1} \quad s.t. \;\; \mathbf{Fs} = y. \quad (11)$$

This convex optimization problem can be solved by linear programming (LP), basic pursuit (BP) and orthogonal matching pursuit (OMP) [23].

III. PROPOSED CHANNEL FEEDBACK SCHEME BASED ON COMPRESSIVE SENSING

In this section, the proposed channel feedback scheme for the RIS assisted wireless communication systems is described. In contrasted to the systems using the sub-GHz band and LTE frequency band with the channel characteristics of the rich scattering environment, the sparse channel characteristics of the mmWave band are considered for the efficient downlink CSI feedback scheme.

A. DOWNLINK CSI COMPRESSION

This paper considers that the downlink CSI is perfectly obtained at the each UE through the downlink channel estimation [18]. Then, the cascaded channel matrix $\mathbf{H}_u$ can be converted to the angular domain cascaded channel matrix $\mathbf{H}_{u,ang} \in \mathbb{C}^{N\times G}$ to utilize the limited propagation environment in angular domain, which is the mmWave channel characteristics, as follows [17], [19],

$$\mathbf{H}_{u,ang} = \mathbf{H}_u\mathbf{U}_M, \quad (12)$$

where $\mathbf{U}_M \in \mathbb{C}^{M\times G}$ is the unitary matrix which is composed of array response vectors. These array response vectors quantize the AoD at BS into G grids, as follows,

$$\mathbf{U}_M = \left[\mathrm{a}_t(\phi_1), \ldots, \mathrm{a}_t(\phi_g), \ldots, \mathrm{a}_t(\phi_G)\right], \quad (13)$$

$$\phi_g = -\frac{\pi}{2} + \frac{\pi}{G}(g-1), \quad (14)$$

where the ϕ_g denotes the angle of quantized AoD. The each column of the $\mathbf{U}_M$ can be generated according to (6) and (14).

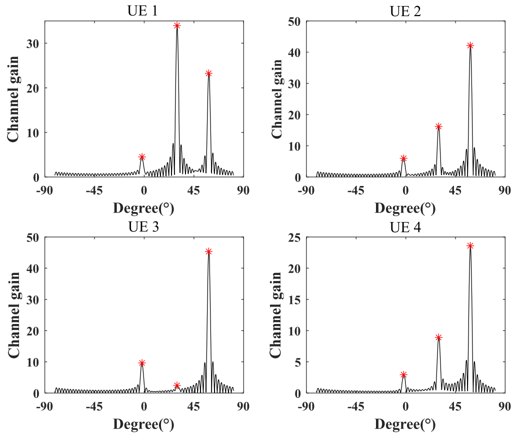

FIGURE 2. **Represents angular domain channel gain versus AoD for the RIS assisted communication systems with M=64, $N = 256$, $U = 4$ and $P_1 = 3$.**

Then, it is worth to note that the $\mathbf{H}_1$ is the channel matrix from BS to RIS and it is information that all UEs share in common. Fig. 2 represents the gain of cascaded angular domain channel matrix for AoD at the BS when $M = 64$, $N = 256$, $U = 4$ and $P_1 = 3$. In Fig. 2, the black line and the red stars denote the channel gain and the real AoD at BS respectively. It is shown that the most of the channel gains are close to zero except for the channel gain at AoD which is common to all UEs. Therefore, the $\mathbf{H}_{u,ang}$ obtained through transformation into the angular domain has a small number of column vectors that have a dominant channel gain.

However, there is a problem in quantizing the obtained column vectors with high accuracy due to the relatively large number of reflective elements in the RIS than the number of BS antennas. For this problem, the CS approach is proposed as follows,

$$\mathbf{s}_{u,p} = \mathbf{T}^{\mathbf{H}}\bar{\mathbf{h}}_{u,p}, \tag{15}$$

$$\bar{y}_{u,p} = \mathbf{A}\mathbf{T}\mathbf{s}_{u,p} = \mathbf{F}\mathbf{s}_{u,p}, \tag{16}$$

where the $\bar{\mathbf{h}}_{u,p} \in \mathbb{C}^{N\times 1}$ denotes the column vector of $\mathbf{H}_{u,ang}$ corresponding to the index of the angle ϕ_{g_p} $(p = 1, \ldots, P_1)$ that it has a dominant channel gain in the quantized AoD set $\{\phi_1, \ldots, \phi_G\}$, $\mathbf{s}_{u,p} \in \mathbb{C}^{N\times 1}$ is the sparsified vector, $\bar{y}_{u,p} \in \mathbb{C}^{L\times 1}$ is the measurement vector with relatively small integer L than N and $\mathbf{A} \in \mathbb{C}^{L\times N}$, $\mathbf{T} \in \mathbb{C}^{N\times N}$ are the measurement matrix and the sparsifying basis respectively. In this paper, the DFT matrix is employed for sparsifying basis $\mathbf{T}$. To achieve optimal performance of CS, KLT matrix is known as optimal sparsifying basis. However, KLT has a significant problem that it is data-dependent [24]. This is unfeasible since cascaded channel $\mathbf{H}_u$ is required on both BS side and UE side to implement the pre-shared KLT sparsifying basis $\mathbf{T}$. Therefore, in this paper, the DFT matrix which is non-data-dependent and has sub-optimal performance is considered as a sparsifying basis $\mathbf{T}$. The elements of the measurement matrix $\mathbf{A}$ are generated randomly according to the Gaussian distribution. Then, for codebook generation, this paper adopts the clustering-based

Algorithm 1 Clustering-Based Codebook Generation

Input Stored measurement vectors set:
$\Theta = \{y_1, \ldots, y_S\} \in \mathbb{C}^L$
Codebook size bits: B
Output Codebook: C

Repeat
Step 1:
Set initial 2^B centroids randomly expressed as
$$I = \{t_1, \ldots, t_{2^B}\} \in \mathbb{C}^L$$
Step 2:
All input vectors are assigned to each centroid as follows
$$b(n) = \underset{j=1,\ldots,2^B}{\arg\min}\{d(y_n, t_j)\}, \quad y_n \in \Theta, t_j \in I$$
Step 3:
Update the centroid of each cluster
$$t_j = mean(\{y_n \in \Theta | b(n) = j\}), \quad j \in \{1, \ldots, 2^B\}$$
Until the centroid of each cluster stops changing
Step 4: $C \leftarrow I$

Algorithm 2 Downlink CSI Compression

Input:
Cascaded channel: $\mathbf{H}_u$
Unitary matrix: $\mathbf{U}_M$
Sparsifying basis: $\mathbf{T}$
Sensing matrix: $\mathbf{F}$
Codebook: $C = [\mathbf{w}_1, \ldots, \mathbf{w}_{2^B}]$
Output:
Codeword index: $F_{u,p}$

```
for u = 1 : U do
    H_{u,ang} = H_u U_M
    Extract dominant column vectors: h̄_{u,p}
    for p = 1 : P_1 do
        s_{u,p} = T^H h̄_{u,p}
        ȳ_{u,p} = F s_{u,p}
        F_{u,p} = arg max_{j=1,...,2^B} |ỹ^H_{u,p} w_j|
    end for
end for
```

algorithm [25]. The clustering-based algorithm is an iterative algorithm to set optimal criteria which minimize the quantization error. The codebook generation procedures are described in Algorithm 1.

Next, by utilizing the generated B-bits resolution codebook $C = [\mathbf{w}_1, \ldots, \mathbf{w}_{2^B}] \in \mathbb{C}^{L\times 2^B}$, the u-th UE computes the codeword index $F_{u,p}$ as follows,

$$F_{u,p} = \underset{j=1,\ldots,2^B}{\arg\max}\left|\tilde{y}^H_{u,p}\mathbf{w}_j\right|, \tag{17}$$

where $\tilde{y}_{u,p} \in \mathbb{C}^{L\times 1}$ denotes the direction of measurement vector $\bar{y}_{u,p}$ and this index is transferred to BS. Therefore, the proposed downlink CSI compression scheme for the RIS assisted communication systems can be described in Algorithm 2.

Algorithm 3 Downlink CSI Recovery

Input:
Codeword index: $F_{u,p}$
Unitary matrix: $\mathbf{U}_M$
Sparsifying basis: $\mathbf{T}$
Sensing matrix: $\mathbf{F} = [\mathbf{f}_1, \ldots, \mathbf{f}_N]$
Codebook: $C = [\mathbf{w}_1, \ldots, \mathbf{w}_{2^B}]$
Index of quantized AoD : g_p
Threshold: ξ
Output:
Reconstructed cascaded channel: $\hat{\mathbf{H}}_u$

for $u = 1 : U$ **do**
  $\hat{\mathbf{H}}_{u,ang} = \mathbf{0}^{N\times G}$
  for $p = 1 : P_1$ **do**
    $\hat{y}_{u,p} = |\bar{y}_{u,p}| \mathbf{w}_{F_{u,p}}$
    Initialize:
    $k = 0, s_0 = 0, r_0 = \hat{y}_{u,p}, \Lambda_0 = \emptyset, \mathbf{F}_0 = \mathbf{0}$
    while $\|\mathbf{r_k}\|_2 > \xi$ **do**
      $k = k + 1$
      $\lambda_k = \arg\max_{j=1,\ldots,N}(\langle \mathbf{r}_{k-1}, \mathbf{f}_j \rangle)$
      $\Lambda_k = \Lambda_{k-1} \cup \{\lambda_k\}$
      $\mathbf{F}_k = [\mathbf{F}_{k-1}\ \mathbf{f}_{\lambda_k}]$
      $\mathbf{s}_k = (\mathbf{F}_k^H \mathbf{F}_k)^{-1} \mathbf{F}_k^H \hat{y}_{u,p}$
      $\mathbf{r}_k = \hat{y}_{u,p} - \mathbf{F}_k \mathbf{s}_k$
    end while
    $\hat{\mathbf{s}}_{u,p} = \mathbf{0}^{N\times 1}$
    $\hat{\mathbf{s}}_{u,p}(\Lambda_k) = \mathbf{s}_k$
    $\hat{\mathbf{h}}_{u,p} = \mathbf{T}\hat{\mathbf{s}}_{u,p}$
    $\hat{\mathbf{H}}_{u,ang}(:, g_p) = \hat{\mathbf{h}}_{u,p}$
  end for
  $\hat{\mathbf{H}}_u = \hat{\mathbf{H}}_{u,ang}\mathbf{U}_M^H$
end for

B. DOWNLINK CSI RECOVERY

The stable downlink CSI recovery scheme is proposed in this subsection. According to the section II-C, in order to stably recover the sparse vector $\hat{\mathbf{s}}_{u,p} \in \mathbb{C}^{N\times 1}$ from the measurement vector $\hat{y}_{u,p} \in \mathbb{C}^{L\times 1}$, the under-determined system needs to solve. In this paper, this problem is solved through the l_1-norm minimization problem by employing the OMP algorithm. Then, the angular domain dominant channel vector $\hat{\mathbf{h}}_{u,p}$ can be reconstructed by utilizing the obtained sparse vector $\hat{\mathbf{s}}_{u,p}$ and the pre-shared sparse basis $\mathbf{T}$ in (15) as follows,

$$\hat{\mathbf{h}}_{u,p} = \mathbf{T}\hat{\mathbf{s}}_{u,p}, \tag{18}$$

where $\hat{\mathbf{h}}_{u,p} \in \mathbb{C}^{N\times 1}$ is reconstructed dominant channel vector in angular domain. Next, the cascaded channel matrix $\mathbf{H}_u$ in (12) is reconstructed as follows,

$$\hat{\mathbf{H}}_u = \hat{\mathbf{H}}_{u,ang}\mathbf{U}_M^H, \tag{19}$$

where $\hat{\mathbf{H}}_{u,ang}$ is reconstructed angular domain cascaded channel matrix which is the column vector that corresponding to the index of the quantized AoD g_p is $\hat{\mathbf{h}}_{u,p}$ and the remainder is the zero-vector.

Finally, the entire channel from BS to the u-th UE through RIS in (2) can be expressed as follows,

$$\begin{aligned}\mathbf{h}_u &= \mathbf{h}_{2,u}^H \Phi \mathbf{H}_1\\ &= \mathbf{v}^T \mathrm{diag}(\mathbf{h}_{2,u}^H)\mathbf{H}_1\\ &= \mathbf{v}^T \hat{\mathbf{H}}_u,\end{aligned} \tag{20}$$

where the phase shift values $\mathbf{v}$ is calculated by exploiting the largest eigenvalue optimization scheme in [5]. Then the downlink CSI recovery procedures are summarized in Algorithm 3.

C. PRECODER DESIGN

In massive MIMO systems, precoders that can be considered are non-linear precoders such as dirty paper coding (DPC) and successive interference cancellation (SIC), and linear precoders such as maximum ratio transmission (MRT), zero-forcing (ZF), and minimum mean squared error (MMSE). The non-linear precoders show optimal performance, but its implementation is unfeasible because of the high computational complexity. In the case of linear precoders, it can be implemented in massive MIMO systems by showing sub-optimal performance with relatively low computational complexity. ZF precoder, which is a linear precoder, can effectively remove inter-user interference in multi-user systems than MRT precoder, which is another linear precoder. Also, ZF precoder has a performance close to MMSE precoder which considers the noise value [26]. Therefore, in this paper, ZF precoder $\mathbf{G} = [\mathbf{g}_1, \ldots, \mathbf{g}_U] \in \mathbb{C}^{M\times U}$ is considered. When the total channel matrix is $\mathbf{H}_{total} = [\mathbf{h}_1, \ldots, \mathbf{h}_U]^T \in \mathbb{C}^{U\times M}$, the ZF precoder $\mathbf{G}$ is expressed as follows,

$$\mathbf{G} = \bar{\mathbf{G}}\sqrt{\mathbf{P}}, \tag{21}$$

$$\mathbf{G} = \bar{\mathbf{G}}\sqrt{\mathbf{P}} \quad s.t.\ \|\mathbf{G}\|_F^2 \le P_{total}, \tag{22}$$

where $\bar{\mathbf{G}}$ is ZF precoding matrix and $\mathbf{P} = \mathrm{diag}(\rho_1, \ldots, \rho_U)$ is power allocation matrix, where ρ_u denotes the transmit power for the u-th UE at the BS. Then, the achievable spectral efficiency is expressed as follows,

$$R = \sum_{u=1}^{U} \log_2(1 + \mathrm{SINR}_u), \tag{23}$$

$$\mathrm{SINR}_u = \frac{|\mathbf{h}_u^T \mathbf{g}_u|^2}{\sigma^2 + \sum_{i=1, i\neq u}^{U} |\mathbf{h}_u^T \mathbf{g}_i|^2}, \tag{24}$$

where $\mathbf{h}_u^T$ is the u-th row vector of the total channel matrix $\mathbf{H}_{total}$, $\mathbf{g}_u$ is the u-th column vector of ZF precoder $\mathbf{G}$. To maximize the achievable spectral efficiency, water-filling power allocation is adopted as follows [27],

$$\rho_u = \frac{1}{v_u}\max\{\mu - v_u\sigma^2, 0\}, \tag{25}$$

TABLE 1. Simulation parameters.

BS-RIS dominant paths	$P_1 = 2$
RIS-UE dominant paths	$P_2 = 4$
Spacing of transmit antennas	0.5λ
Spacing of RIS elements	0.5λ
Compression ratio	$L/N = 0.25$
AoD quantization grid	$G = 2^{10}$
Threshold	$\xi = 10^{-4}$

where v_u is the u-th diagonal element of $\bar{\mathbf{G}}^H\bar{\mathbf{G}}$ and μ is determined as $\sum_{u=1}^{U} \max\{\mu - v_u\sigma^2, 0\} = P_{total}$.

D. COMPUTATIONAL COMPLEXITY

In this subsection, the computational complexity based on Big-O notation is discussed. Big-O notation is used to compare computational complexity between algorithms. The complexity of the proposed compressive sensing based channel feedback (CSFB) scheme and the conventional dimension reduced channel feedback (DRFB) scheme can be simply expressed as below. In CSFB, the computational complexity of downlink CSI compression can be calculated as $\mathcal{O}(NMG + P_1(LN + L2^B))$. Then, the computational complexity of downlink CSI recovery is given by $\mathcal{O}(U(NMG + P_1(L + LNK)))$, where K denotes the number of iterations until the OMP algorithm converges. In DRFB, the computational complexity of downlink CSI compression and downlink CSI recovery can be shown as $\mathcal{O}(NMG + P_1(GNP_2 + (NP_2^2 + N)2^B))$ and $\mathcal{O}(U(NMG + P_1N))$ respectively. In the environment with $M = 16$ and $N = 256$, the CSFB scheme reduced the computational complexity by 15% compared to the conventional scheme, and the computational complexity in the $N = 64$ environment was reduced by 32%.

IV. SIMULATION RESULTS

In this section, the simulation results of proposed channel feedback scheme for RIS assisted wireless communication systems are presented. The proposed compressive sensing based channel feedback (CSFB) scheme is compared to the channel state information at the transmitter (CSIT) and the dimension reduced channel feedback (DRFB) scheme in [19]. In this simulation, to reflect the sparsity of the mmWave propagation environment, the number of dominant channel paths between BS and RIS and between RIS and each UE are set as $P_1 = 2$ and $P_2 = 4$, respectively. The BS-RIS channel is set to the line-of-sight (LoS) channel with a Rician K-factor of 15 dB, and the RIS-UEs channel is set to the non-LoS (NLoS) channel. The BS-UEs direct channel is blocked by the obstacles. Also, this simulation considers the RIS assisted wireless communication system that the transmit antennas with ULA configurations and the RIS elements with UPA configurations are deployed and each spacing of the transmit antennas and the RIS elements is half wavelength. The compression ratio is set as $L/N = 0.25$, the AoD quatization grid is set as $G = 2^{10}$ and the threshold is set as $\xi = 10^{-4}$. The simulation parameters are presented in Tab. 1.

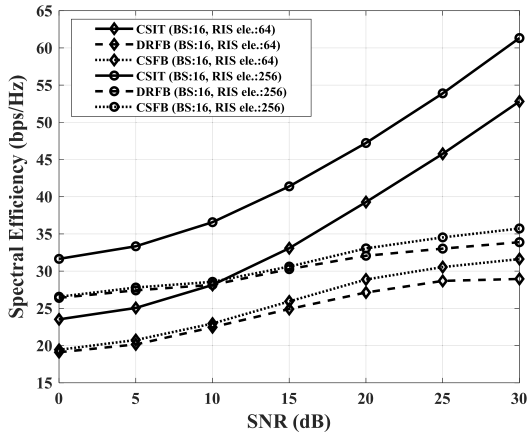

FIGURE 3. Spectral efficiency according to SNR(dB) for RIS assisted MU-MIMO systems when $M = 16$, $N = 64, 256$, $U = 4$ and $B = 10$.

In this paper, to evaluate the performance of proposed scheme, the achievable spectral efficiency in (23) is adopted. Fig. 3 shows the spectral efficiency of the perfect CSIT environment and imperfect CSIT environment with DRFB scheme and proposed CSFB scheme according to SNR. In Fig. 3, the number of BS antennas of $M = 16$, the number of RIS elements of $N = 64, 256$, the number of single-anatenna user of $U = 4$ and the codebook resolution bits of $B = 10$ are considered. To achieve high spectral efficiency, the large number of RIS elements N is necessary. However, in this case, the DRFB scheme has an N-dimensional vector quantization problem with $\mathcal{O}(N2^B)$ which has high computational complexity and quantization error. In contrast, the proposed CSFB scheme provides improved performance compared to the DRFB scheme. The proposed scheme has a reduced computational complexity and quantization error by performing relatively low L-dimensional vector quantization with $\mathcal{O}(L2^B)$. In the results, Fig. 3 presents that the proposed CSFB scheme shows improved performance compared to the conventional scheme even when N is increased. At lower values of SNR, there is hardly a difference in performance between the CSFB scheme and DRFB scheme, whereas at higher values of SNR, the proposed CSFB scheme shows improved performance. This result occurs since at a low SNR values, the noise values have a dominant effect on the performance, and the performance is not sensitive to the accuracy of the channel feedback scheme. However, at a high SNR value, the performance relies on the accuracy of the channel feedback scheme since the inter-user interference has a dominant effect. Also, in Fig. 3, the performances of the imperfect CSIT environment are relatively low compared to the perfect CSIT environment. This problem occurs since the recovery of the perfect downlink CSI with the channel feedback scheme at the BS is impractical. Therefore, the imperfect CSIT environment has a problem derived from inter-user interference $\sum_{i=1, i\neq u}^{U} \left|\mathbf{h}_u^T \mathbf{g}_i\right|^2$

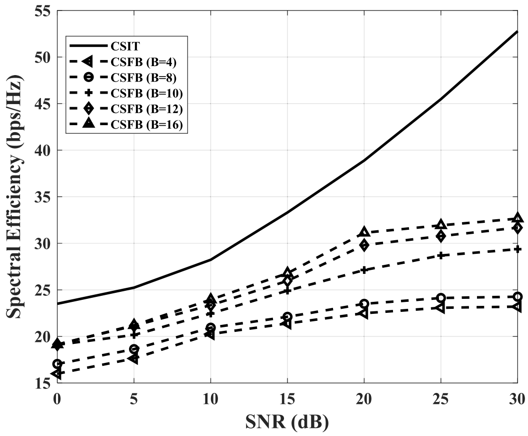

FIGURE 4. Spectral efficiency according to SNR(dB) for RIS assisted MU-MIMO systems when $M = 16$, $N = 64$ and $U = 4$.

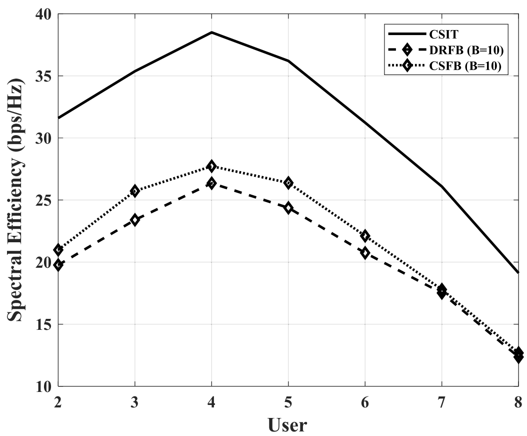

FIGURE 5. Spectral efficiency according to the number of UEs for RIS assisted MU-MIMO systems when $M = 16$, $N = 64$ and $B = 10$.

in (24) which is imperfectly eliminated and this problem leads degradation of the spectral efficiency.

Fig. 4 shows the spectral efficiency of the perfect CSIT environment and the imperfect CSIT environment with CSFB scheme varying the codebook resolution bits B. In Fig. 4, $M = 16$, $N = 64$, $U = 4$ and $B = 4, 8, 12, 16$ are considered. In the results, when B increase, the performance of channel feedback scheme also increase. By utilizing the large size of codebook, the complex unit sphere is clustered more specifically. Therefore, the quantization error is reduced and the BS can acquire more reliable downlink CSI. However, when the size of codebook increases, the computational complexity also increases exponentially for codeword searching procedure. Fig. 4 presents that the spectral efficiency increases when B varies from 4 to 16. When the codebook resolution bit B increases from 4 to 8, the increase of performance is not large. On the other hand, when B increases from 8 to 10, the increase of performance is large since the quantization error decreases as the codebook size increases exponentially. However, if B is sufficiently large, the increase of performance gradually decreases and converges. The proposed scheme requires a computational

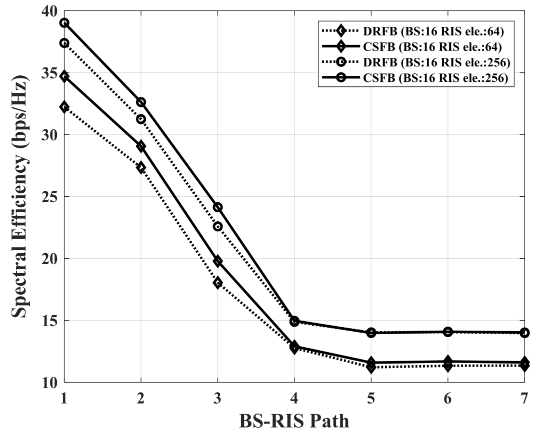

FIGURE 6. Spectral efficiency according to the number of dominant BS-RIS paths for RIS assisted MU-MIMO systems when $M = 16$, $N = 64, 256$, $U = 4$ and $B = 10$.

complexity of $\mathcal{O}(L2^B)$ in the codebook searching procedure. If B is less than 10, the channel feedback scheme shows poor performance. However, when B is greater than 10, the performance does not increase in proportion to the increase in computational complexity. Therefore, in this paper, when the performance and the computational complexity are considered, the codebook resolution bit is set as $B = 10$ to evaluate the performance of channel feedback schemes.

Fig. 5 shows the effect of the number of UEs on the spectral efficiency performance with $M = 16$, $N = 64$, $B = 10$ and SNR $=$ 20dB. It is shown that the proposed CSFB scheme presents improved performance than the DRFB scheme for the RIS assisted MU-MIMO communication systems. In the results, Fig. 5 presents that the number of UEs is larger than 4 and the spectral efficiency is decreased in both perfect CSIT and imperfect CSIT environments. This problem is derived from the rank-deficiency of the channel matrix $\mathbf{H}_{total}$ which is common property of massive MIMO channel with limited scattering environment, specifically in the mmWave communication systems.

Fig. 6 shows the spectral efficiency performance according to the number of dominant paths between the BS and the RIS when $M = 16$, $N = 64, 256$, $B = 10$, $U = 4$ and SNR $=$ 20dB. It is shown that proposed scheme achieves improved performance in the limited scattering environment which has the small number of dominant BS-RIS paths. However, there is performance degradation when the number of dominant BS-RIS paths is increased. The angular domain channel matrix $\mathbf{H}_{u,ang}$ has the most of channel gain in the column vectors corresponding to AoD. Thus, when the number of dominant paths is increased, the channel gain is distributed. Therefore, the channel gain corresponding to the channel vectors which exclude the feedback channel vectors $\bar{\mathbf{h}}_{u,p}$ increases in proportion to the number of dominant paths and this problem increases the performance loss.

Fig. 7 presents the spectral efficiency performance according to the number of RIS elements for $M = 16$, $B = 10$, $U = 4$ and SNR $=$ 30dB. In the results, when the number of

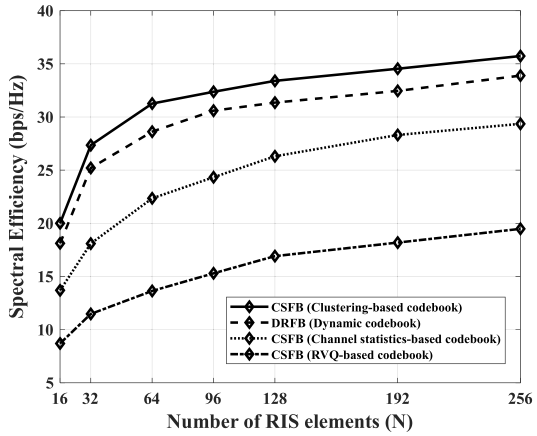

FIGURE 7. Spectral efficiency according to the number of RIS elements for RIS assisted NU-MIMO systems when $M = 16$, $U = 4$ and $B = 10$.

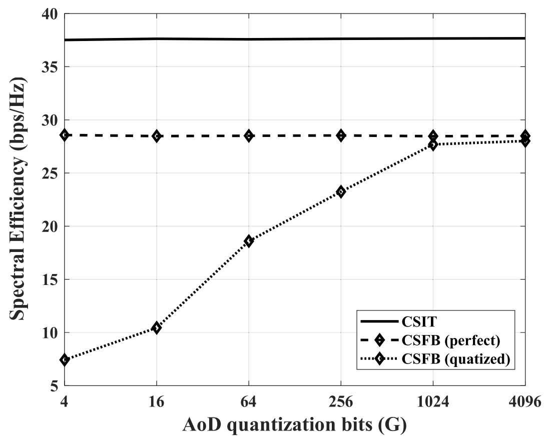

FIGURE 8. Spectral efficiency according to the AoD quantization resolution for RIS assisted NU-MIMO systems when $M = 16$, $N = 64$, $U = 4$ and $B = 10$.

RIS elements increases, the spectral efficiency performance of all schemes is increased. In particular, the performance of the CSFB scheme with the clustering-based codebook shows the improved spectral efficiency compared to other schemes with different codebooks since the non-linear quantization-based codebook can quantize vectors more efficiently.

Finally, Fig. 8 shows the spectral efficiency according to the AoD quantization resolution G for $M = 16, N = 64, B = 10$, $U = 4$ and SNR $= 20$dB. In the results, Fig. 7 presents that the spectral efficiency is improved when the AoD quantization resolution G is increased since the accurate AoD information is necessary for extracting $\bar{\mathbf{h}}_{u,p}$ which is dominant channel gain vector in angular domain channel matrix $\mathbf{H}_{u,ang}$. In particular, when the G is sufficiently large, the performance is converged on the performance using perfect AoD information.

V. CONCLUSION

This paper proposes the limited channel feedback scheme for RIS assisted MU-MIMO wireless communication systems. In order to alleviate the channel feedback problem which is derived from the large number of reflective elements in RIS occurs, by utilizing sparse nature of mmWave propagation environment, compressive sensing based channel feedback scheme is proposed. In the proposed scheme, the downlink CSI is quantized at the UEs with clustering-based codebook and the only small number of index is transferred to the BS. Then, the BS reconstructs the reliable downlink CSI with OMP algorithm. Simulation results show the spectral efficiency performance of proposed scheme. The proposed scheme achieves up to 10% improved performance with about 30% reduction in computational complexity compared to conventional scheme in multi-user and limited scattering environment.

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