Efficient Transmission and Detection Based on RNS for Generalized Space Shift Keying

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***Abstract*—We propose an efficient transmission scheme for the generalized space shift keying (GSSK) based on the residue number system (RNS). The proposed scheme increases the number of active transmit antenna combinations (TACs), resulting in a higher throughput than that of the conventional GSSK systems. The received signals can be detected by a joint maximum likelihood (ML) detection, whose complexity, however, grows exponentially with the number of active TACs. To solve this problem, we propose a new detection method based on the RNS, whose complexity is much lower than that of the joint ML detection with negligible performance loss.**

***Index Terms*—Multi-input multi-output, generalized space shift keying, residue number system, maximum likelihood detection, mixed radix conversion.**

I. Introduction

SPACE shift keying (SSK) [1]–[4] is a low-complexity multi-input multi-output (MIMO) technique which employs only one active transmit antenna (TA) in each time slot. In the SSK system, information is conveyed only through the indices of active TAs. The special structure of SSK offers inherent robustness to inter-channel interference (ICI). However, a disadvantage of SSK lies in that the throughput increases with the base-two logarithm of the number of TAs N_T.

In order to increase the throughput, the generalized space shift keying (GSSK) [5] is proposed to enable N_P active TAs in each time slot. Hence, the throughput of the GSSK system is directly related to the number of TA combinations (TACs). Specifically, for a conventional GSSK system with N_P out of N_T active antennas, the number of active TACs is $2^{\lfloor \log_2 K_C \rfloor}$, where $K_C = \binom{N_T}{N_P}$. It is possible to transmit more bits by increasing the number of active TACs.

The residue number system (RNS) [6] has received broad attention in digital signal processing [7] and communications [8]. RNS tells that a non-negative integer I can be uniquely reconstructed from its remainders $z_1, z_2, \ldots, z_Q$ by,

$$z_i = I \mod M_i, \tag{1}$$

if $I < \prod_{i=1}^{Q} M_i$, where all moduli M_i are co-prime.[1] Motivated by this property, we propose a RNS based GSSK (RNS-GSSK) transmission scheme to increase the number of active TACs and equivalently the throughput of the GSSK systems. The GSSK systems can be detected by a joint maximum likelihood (ML) [9] detection algorithm. However, the computational complexity of the joint ML detection grows exponentially with the number of TACs, which makes the joint ML detector impractical for a large number of TACs. Aiming at low computation cost, we further propose a RNS based ML (RNS-ML) detection algorithm. In detail, the contributions of this letter can be summarized as:

- The proposed RNS based transmission scheme can increase the throughput of the GSSK system.
- The proposed RNS-ML algorithm can reduce the computational complexity of signal detection for the RNS-GSSK system with negligible performance loss.

The rest of this letter is organized as follows. In Section II, we introduce the GSSK system model and the joint ML detection. Our proposed RNS-GSSK system and throughput analysis are introduced in Section III. In Section IV, the RNS-ML detection algorithm and the complexity analysis are provided. Performance comparisons of the RNS-GSSK systems and the MIMO systems are presented in Section V. Finally, Section VI concludes this letter.[2]

II. GSSK System of Q Time Slots

A GSSK system consists of a MIMO wireless link with N_T TAs and N_R receive antennas. In this letter, we consider a GSSK system transmitting the source information $\mathbf{b} = [b_1, \ldots, b_L]$ in Q time slots, where $b_i \in \{0, 1\}, i = 1, \ldots, L$.

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[1] M_i, M_j are co-prime to each other if $\gcd(M_i, M_j) = 1$, where $i \neq j$ and gcd stands for the greatest common divisor.

[2] *Notations*: Bold lowercase and capital letters are used for vectors and matrices, respectively. $(\cdot)^H$ denotes Hermitian transposition. A complex Gaussian distribution with mean u and variance σ^2 is denoted by $\mathcal{CN}(u, \sigma^2)$. $\lfloor \cdot \rfloor$ denotes flooring operation. $\binom{\cdot}{\cdot}$ denotes the binomial coefficient. A hat over the variable name is used to signify the detected signals. $\| \cdot \|$ denotes the Frobenius norm of a vector.

TABLE I
AN EXAMPLE OF RNS BASED TRANSMISSION SCHEME FOR $N_T = 16, N_P = 2, Q = 2, M_1 = 69, M_2 = 119$

Source Information $\mathbf{b}$	TAC index I	$(\mathbf{z}_1, \mathbf{z}_2)$
0000000000000	0	$(0, 0)$
0000000000001	1	$(1, 1)$
⋮	⋮	⋮
0000001000100	68	$(68, 68)$
0000001000101	69	$(0, 69)$
⋮	⋮	⋮
1111111111110	8190	(49,99)
1111111111111	8191	(50,100)

If $Q = 1$, the corresponding GSSK system degenerates into the conventional GSSK system [5]. The source information $\mathbf{b}$ is mapped into an index of TAC I, which is used for selecting N_P active antennas in each of Q time slots. When we choose N_P from N_T antennas as the active antennas, the number of possible TACs in each time slot is K_C. In GSSK systems, the number of total active TACs in Q time slots, denoted by T, must be a power of two to modulate the binary information bits $\mathbf{b}$. Therefore, there are at most $T = 2^{\lfloor Q \log_2 K_C \rfloor}$ active TACs and $0 \leq I \leq 2^{\lfloor Q \log_2 K_C \rfloor} - 1$. Consequently, at most $L = \lfloor Q \log_2 K_C \rfloor$ bits could be conveyed on the indices of TACs in Q time slots.

In the i-th time slot, the N_P active antennas correspond to a constellation vector $\mathbf{x}_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,N_T}]^T$, in which there are N_P non-zero values and $N_T - N_P$ zeros. Let $\mathbf{H}_i \in \mathbb{C}^{N_R \times N_T}$ be the MIMO channel matrix from the transmitter to the receiver in the i-th time slot, whose entries follow $\mathcal{CN}(0, 1)$. Then, the received signal in the i-th time slot can be formulated as

$$\mathbf{y}_i = \sqrt{\frac{\rho}{N_P}} \mathbf{H}_i \mathbf{x}_i + \boldsymbol{\eta}_i, \tag{2}$$

where ρ denotes the average signal to noise ratio (SNR) at each receive antenna and $\boldsymbol{\eta}_i \in \mathbb{C}^{N_R \times 1}$ denotes the noise vector whose elements follow $\mathcal{CN}(0, \sigma^2)$.

In [9], a joint ML detection was applied to space-time shift key system, which can also be applied to estimate the index $\hat{I}$ of the active TAC in the RNS-GSSK system as

$$\hat{I} = \arg\min_{\hat{I} \in \mathbb{I}} \sum_{i=1}^{Q} \| \mathbf{y}_i - \mathbf{H}_i \mathbf{x}_i \|^2, \tag{3}$$

where $\mathbb{I} = \{0, 1, \ldots, T - 1\}$.

III. GSSK TRANSMISSION BASE ON RNS

RNS is a number system which divides a large integer into smaller integers with a specific moduli set. In this section, we will introduce the RNS-GSSK to increase the throughput of the GSSK system.

Algorithm 1 RNS Based GSSK Transmission Scheme

Initialization:
Given Q, N_T and N_P, select $\{M_1, \ldots, M_Q\}$ by exhaustive search such that constraints (A) and (B) are satisfied.
Converting:
Map information $\mathbf{b}$ to I by (4).
for $i = 1$ to Q **do**
  Convert I into RNS $\mathbf{z}_i$ by (1).
end for
Transmission:
Transmit the symbols $\mathbf{x}_i$ according to z_i.

A. RNS Based Transmission Scheme

We first map the source information $\mathbf{b}$ into an active TAC index I by

$$I = \sum_{i=1}^{L} b_i \cdot 2^{i-1}, \tag{4}$$

and convert I into the RNS residues $\mathbf{z} = [z_1, z_2, \ldots, z_Q]$ by (1), where z_i will be used as the index of the active TAC in the i-th time slot. For example, the results of above process for $N_T = 16, N_P = 2, Q = 2, M_1 = 69, M_2 = 119$ are shown in Table I. Then, the constellation vectors $\mathbf{x}_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,N_T}]^T$ corresponding to z_i are transmitted, where I is the index of the TAC for $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_Q$ and z_i is obtained by (1).

In the RNS-GSSK system, each moduli M_i should satisfy the following two constraints:

(A) $K_U < M_i \leq K_C$, where $K_U = 2^{\lfloor \log_2 K_C \rfloor}$ is the number of TACs in conventional GSSK;
(B) $\gcd(M_i, M_j) = 1$, where $i \neq j$ and gcd stands for the greatest common divisor.

The first constraint is for increasing active TACs to improve the throughput of the RNS-GSSK system, while the second one is for reconstructing $\hat{I}$ by the RNS-ML algorithm, which will be introduced in the next section. The values of $\{M_1, \ldots, M_Q\}$ can be selected by an off-line exhaustive search in the range $[K_U, K_C]$, and should be chosen large enough to transmit more bits, meanwhile $\prod_{i=1}^{Q} M_i$ must be as small as possible. The RNS based GSSK transmission scheme is given in **Algorithm 1**.

B. System Throughput

In conventional GSSK systems, the index of TAC in each time slot carries $\lfloor \log_2 K_C \rfloor$ bits. Therefore, the throughput of the conventional GSSK is $R_{GSSK} = \lfloor \log_2 K_C \rfloor$ (bpcu).

In the RNS-GSSK system, the number of antenna combinations is $\prod_{i=1}^{Q} M_i$. Therefore, the antenna combinations in Q time slots can convey $\lfloor \log_2 \prod_{i=1}^{Q} M_i \rfloor$ bits, resulting in the throughput of the RNS-GSSK system $R_{RNS} = \frac{\lfloor \log_2 \prod_{i=1}^{Q} M_i \rfloor}{Q}$.

Letting $R_D = R_{RNS} - R_{GSSK}$ denote the throughput improvement, we have $R_D = \frac{\lfloor \sum_{i=1}^{Q} \log_2 M_i \rfloor}{Q} - \lfloor \log_2 K_C \rfloor$. From constraint (A) $K_U < M_i$, we have $Q \lfloor \log_2 K_C \rfloor < \log_2 M_1 + \ldots +$

Algorithm 2 MRC Based RNS-ML Detection Algorithm

Detecting Process:
for $i = 1$ to Q **do**
  Search the active TAC $\hat{z}_i$ by (8).
end for
Obtain the coefficients $[\alpha_1, \ldots, \alpha_Q]$ from $\hat{\mathbf{z}}$ by (9)-(11).
Compute antenna combination $\hat{I}$ by (12).
Demapping:
Demap $\hat{I}$ to $\mathbf{b}$ by applying decimal to binary conversion.

$\log_2 M_Q = \sum_{i=1}^{Q} \log_2 M_i$, and hence

$$R_D = \frac{\left\lfloor \sum_{i=1}^{Q} \log_2 M_i \right\rfloor}{Q} - \lfloor \log_2 K_C \rfloor \geq 0. \quad (5)$$

From constraint (A) $M_i \leq K_C$ and constraint (B) $M_i \neq M_j$, we have $\left\lfloor \sum_{i=1}^{Q} \log_2 M_i \right\rfloor < \lfloor Q \log_2 K_C \rfloor$, and therefore

$$R_D < \frac{\lfloor Q \log_2 K_C \rfloor}{Q} - \lfloor \log_2 K_C \rfloor < 1. \quad (6)$$

By combining both of (5) and (6), we have

$$0 \leq R_D < 1. \quad (7)$$

Consider $N_T = 16, N_P = 2$ and $Q = 2$. The throughput of the conventional GSSK system is $R_{GSSK} = \lfloor \log_2 \binom{16}{2} \rfloor = 6$ bpcu. However, the throughput of the RNS-GSSK system is $R_{RNS} = (\lfloor 2 \cdot \log_2 \binom{16}{2} \rfloor)/2 = 6.5$ bpcu.

IV. Low Complexity Detection

A. RNS-ML Detection Algorithm

In the RNS-ML detection, we search for the active TAC $\hat{z}_i$ in the i-th time slot by a conventional ML detection

$$\hat{z}_i = \arg\min_{z_i} \| \mathbf{y}_i - \mathbf{H}_i \mathbf{x}_i \|^2, \quad (8)$$

whose complexity only grows exponentially with K_C. After that, we need to convert $\hat{\mathbf{z}} = [\hat{z}_1, \hat{z}_2, \ldots, \hat{z}_Q]$ to $\hat{I}$. In RNS systems, there are basically two techniques that can be used for this conversion: One is the mixed radix conversion (MRC) [10] and the other is the Chinese remainder theorem (CRT) [11]. In this letter, we only consider MRC. The CRT may also be applied here in a straightforward manner.

We first obtain the coefficients $[\alpha_1, \alpha_2, \ldots, \alpha_Q]$ from $\hat{\mathbf{z}}$ by

$$\alpha_1 = \hat{z}_1 \mod M_1, \quad (9)$$

$$\alpha_2 = \frac{\hat{z}_2 - \alpha_1}{M_1} \mod M_2, \quad (10)$$

$$\vdots$$

$$\alpha_Q = \frac{\hat{z}_Q - \sum_{i=1}^{Q-1} \left(\alpha_i \prod_{j=1}^{i-1} M_j \right)}{\prod_{i=1}^{Q-i} M_i} \mod M_Q. \quad (11)$$

Then, we estimate the active TAC index of Q time slots by

$$\hat{I} = \sum_{i=1}^{Q} \left(\alpha_i \prod_{j=1}^{i-1} M_j \right). \quad (12)$$

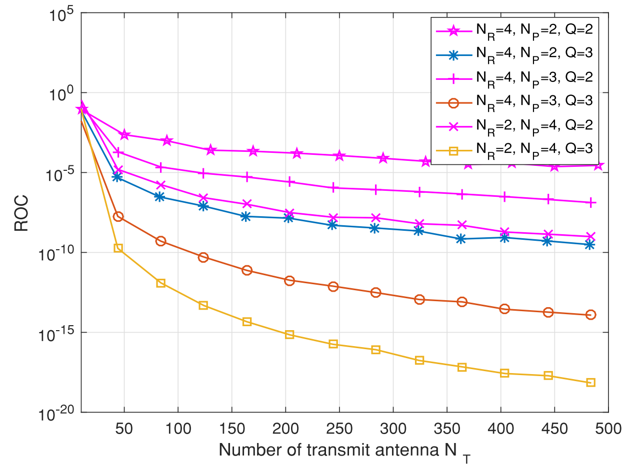

Fig. 1. ROC of the RNS-ML detection to the joint ML detection.

After that, we demap $\hat{I}$ to the information bits $\hat{\mathbf{b}}$. Note that $\hat{I}$ can be obtained only if the constraint (B) is satisfied. Otherwise, two different I's may have the same RNS values $\mathbf{z}$, which makes it impossible to obtain the correct $\hat{I}$ based on MRC [10]. The proposed transmission scheme has negligible performance loss with respect to the ML detection as any small error in detecting $\hat{z}_i$ may cause a larger error in $\hat{I}$. The proposed RNS-ML detection is described in Algorithm 2.

B. Computational Complexity

We compare the complexity of the RNS-ML detector with that of the joint ML detector for RNS-GSSK. To estimate the computational complexity, we use the number of multiplications required in the detection process as in [12]. The number of additions can be shown to have a similar view.

In the RNS-ML detection, the norm $\| \mathbf{y}_i - \mathbf{H}_i \mathbf{x}_i \|^2$ in (8) needs $N_P + 2$ multiplications, which is calculated $N_R M_i$ times to detect each $\hat{z}_i$. On the other hand, $\frac{(Q-1)Q}{2}$ multiplications are required to compute $\alpha_1, \alpha_2, \ldots, \alpha_Q$ [10]. Therefore, the total number of multiplications in the RNS-ML detector is

$$C_{RNS} = \sum_{i=1}^{Q} N_R M_i (N_P + 2) + \frac{(Q-1)Q}{2}. \quad (13)$$

In the joint ML detection, the norm $\| \mathbf{y}_i - \mathbf{H}_i \mathbf{x}_i \|^2$ needs $N_P + 2$ multiplications, which is calculated $N_R T$ times. Therefore, the total number of multiplications in the joint ML detector is

$$C_{Joint} = N_R T (N_P + 2). \quad (14)$$

For comparison purpose, we resort to the ratio of the complexity (ROC)

$$ROC = \frac{C_{RNS}}{C_{Joint}} = \frac{\sum_{i=1}^{Q} N_R M_i (N_P + 2) + \frac{(Q-1)Q}{2}}{N_R T (N_P + 2)}. \quad (15)$$

The ROCs for different configurations are given in Fig. 1. It can be seen that the ROC decreases with the increase of N_T, N_P, N_R and Q.

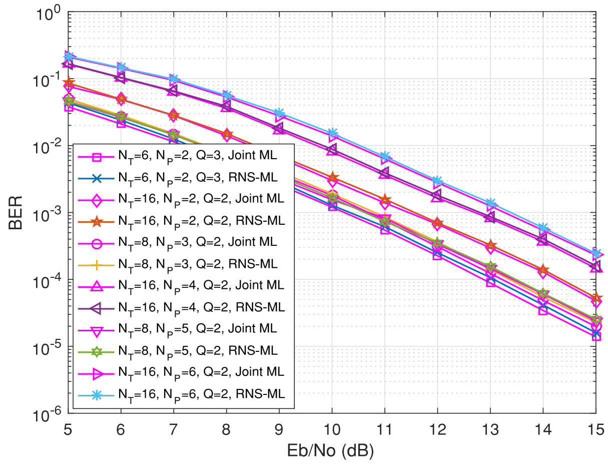

Fig. 2. BER performance comparison of the RNS-GSSK system with joint ML detector and RNS-ML detector ($N_R = 4$).

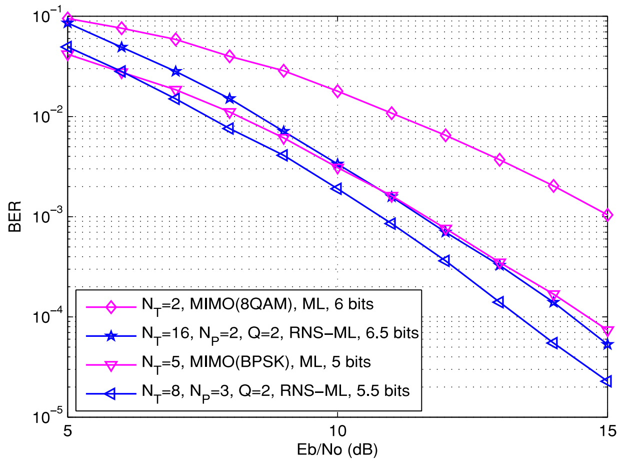

Fig. 3. BER performance comparison of the RNS-GSSK system versus V-BLAST ($N_R = 4$).

V. Simulation Results

Example 1: The bit error rate (BER) performance of RNS-GSSK systems with the RNS-ML detection is shown in Fig. 2. For $N_T = 6, N_P = 2, Q = 3$, we set the moduli $M_1 = 11, M_2 = 13$ and $M_3 = 15$. For $N_T = 16, N_P = 2, Q = 2$, we set the moduli $M_1 = 69$ and $M_2 = 119$. For $N_T = 8, N_P = 3, Q = 2$, we set the moduli $M_1 = 41$ and $M_2 = 50$. For $N_T = 16, N_P = 4, Q = 2$, we set the moduli $M_1 = 1417$ and $M_2 = 1480$. For $N_T = 8, N_P = 5, Q = 2$, we set the moduli $M_1 = 41$ and $M_2 = 50$. For $N_T = 16, N_P = 6, Q = 2$, we set the moduli $M_1 = 5419$ and $M_2 = 6192$. For comparison purpose, the BER performance of the RNS-GSSK systems with the joint ML detector is also shown. It can be seen that our proposed RNS-ML detector can achieve similar performance to that of the joint ML detector. However, we can see that the computational complexity of RNS-ML detector is much lower than that of the joint ML detector, which indicates that the proposed RNS-ML detection algorithm can achieve better performance-complexity tradeoff than the ML detector.

Example 2: In Fig. 3, the BER performance comparison between RNS-GSSK and MIMO systems is made. For $N_T = 8, N_P = 3, Q = 2$, the throughput of the RNS-GSSK system is 5.5 bpcu. For comparison, the throughput of MIMO system with BPSK and $N_T = 5$ is 5.0 bpcu. For $N_T = 16$, $N_P = 2, Q = 3$, the throughput of the RNS-GSSK system is 6.5 bpcu. For comparison, the throughput of MIMO system with 8QAM and $N_T = 2$ is 6.0 bpcu. It is observed from Fig. 3 that the RNS-GSSK system of greater throughputs provides a significant performance gain over the MIMO systems.

VI. Conclusion

In this letter, we have introduced the RNS based GSSK system which is referred to as the RNS-GSSK system. The RNS-GSSK system has more TACs in Q time slots and therefore higher throughput than the GSSK system. In order to reduce the detection complexity, we have also proposed the RNS-ML detection for the RNS-GSSK system. With the proposed RNS-ML detector, the computational complexity of the detection in the RNS-GSSK system can be reduced significantly with negligible performance loss.

References

[1] J. Jeganathan, A. Ghrayeb, L. Szczecinski, and A. Ceron, "Space shift keying modulation for MIMO channels," *IEEE Trans. Wireless Commun.*, vol. 8, no. 7, pp. 3692–3703, Jul. 2009.
[2] P. Yang, M. Di Renzo, Y. Xiao, S. Li, and L. Hanzo, "Design guidelines for spatial modulation," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 6–26, 1st Quart., 2015.
[3] M. Wen, X. Cheng, and L. Yang, *Index Modulation for 5G Wireless Communications* (Wireless Network Series). Berlin, Germany: Springer, 2017.
[4] E. Basar, "Index modulation techniques for 5G wireless networks," *IEEE Commun. Mag.*, vol. 54, no. 7, pp. 168–175, Jul. 2016.
[5] J. Jeganathan, A. Ghrayeb, and L. Szczecinski, "Generalized space shift keying modulation for MIMO channels," in *Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun.*, Cannes, France, Sep. 2008, pp. 1–5.
[6] H. L. Garner, "The residue number system," *IRE Trans. Electron. Comput.*, vol. EC-8, no. 2, pp. 140–147, Jun. 1959.
[7] C.-H. Chang, A. S. Molahosseini, A. A. E. Zarandi, and T. F. Tay, "Residue number systems: A new paradigm to datapath optimization for low-power and high-performance digital signal processing applications," *IEEE Circuits Syst. Mag.*, vol. 15, no. 4, pp. 26–44, Nov. 2015.
[8] A. Sengupta and B. Natarajan, "Performance of systematic RRNS based space-time block codes with probability-aware adaptive demapping," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 2458–2469, May 2013.
[9] S. Sugiura, S. Chen, and L. Hanzo, "Coherent and differential space-time shift keying: A dispersion matrix approach," *IEEE Trans. Commun.*, vol. 58, no. 11, pp. 3219–3230, Nov. 2010.
[10] K. A. Gbolagade, "Effective reverse conversion in residue number system processors," Ph.D. dissertation, Elect. Eng., Math. Comput. Sci., Delft Univ. Technol., Delft, The Netherlands, Feb. 2010.
[11] W. Wang, X. Li, W. Wang, and X.-G. Xia, "Maximum likelihood estimation based robust Chinese remainder theorem for real numbers and its fast algorithm," *IEEE Trans. Signal Process.*, vol. 63, no. 13, pp. 3317–3331, Jul. 2015.
[12] J. Wang, S. Jia, and J. Song, "Generalised spatial modulation system with multiple active transmit antennas and low complexity detection scheme," *IEEE Trans. Wireless Commun.*, vol. 11, no. 4, pp. 1605–1615, Apr. 2012.