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Adaptive Detector Selection for Queue-Stable Word Error Rate Minimization in Connected Vehicle Receiver Design

Minseok Choi, Joongheon Kim, *Member, IEEE,* and Jaekyun Moon, *Fellow, IEEE*

***Abstract*—High-speed and low-latency communications are one of the major requirements for connected vehicle environments. Safety messages in vehicular networks must arrive on time for each vehicle, and the optimization of driving paths also strongly depends on low-latency traffic information. To comply with the demands, a base station take important roles to provide a short service delay for the vehicles, even at the expense of performance. The relationship between delay time and decoding performance at receiver sides in physical layers can be explained by the performance/complexity tradeoff as follows: To achieve better performance in terms of the minimization of word error rates in decoding, the receiver usually requires higher complexity which results in larger delays. We analyze this tradeoff based on the receiver queue model. This paper proposes a novel algorithm to adaptively select one of receiver candidates under the constraint of queue stability so as not to degrade low-latency communications. Based on the configurable architecture for MIMO detectors, this paper shows the proposed algorithm works well on adaptive MIMO detector selection.**

***Index Terms*—Connected vehicles, Low-latency communications, Performance/complexity tradeoff, Adaptive detector selection.**

I. Introduction

In connected vehicles environments [1]–[3], a cellular base station (BS) has to deal with the heavy load of information delivered from a large number of vehicles especially in dense urban areas. In the research domain, interference occurs in frequency domain due to Doppler effects, thus inter-carrier-interference cancellation schemes have been proposed [4] and index-modulated OFDM is also proposed for improving spectral efficiency and link reliability [5]. In general, vehicular messages could be divided into safety and traffic information. Two main types of safety messages are cooperative awareness messages (CAMs) and decentralized environmental notification messages (DENMs); and traffic information includes floating car data (FCD) [2], [3]. While DENMs are event-driven, CAMs are periodic short messages which report user vehicles' status information such as positions and speeds. Similar to CAMs, FCD also requires periodic transmissions of traffic information from vehicles to their associated BSes for optimizing the driving paths. When a BS serves a massive number of vehicles, frequent transmissions of CAMs and FCD may result in system overloads. However, safety information must be received and responded by vehicles in a short time, thus low-latency communication is mandatory for connected vehicles environments.

The relationship between delay and performance in low-latency communications can be explained in some ways through the performance/complexity tradeoff of the receiver processing in the physical layer. In general, higher complexity in receivers often means better performance in terms of word error rate minimization for decoding. However, a high-complexity receiver usually takes longer data processing time which introduces system delays. In this respect, it is important to select a receiver type according to the delay constraints of low-latency delay-sensitive communication systems.

In this paper, performance/complexity tradeoff is analyzed based on the receiver queue model in connected vehicle networks. A high-complexity receiver takes longer data processing time, resulting in an increased queue backlog. In this case, there is a risk of queue overflow, which is fatal to delay-sensitive services. Therefore, this paper proposes an algorithm to adaptively select one of the receiver candidates under the constraint of queue stability so as to facilitate low-latency communications while aiming at the *time-average word error rate (WER) minimization*.

The performance/complexity tradeoffs of various multi-input multi-output (MIMO) detector techniques have been investigated [6]. Recently, the configurable architectures for MIMO detectors which can run a variety of detection schemes have been getting a lot of attention in both industry and academia [7], [8]. These detector designs enable the performance/complexity tradeoff to be adjusted depending on received signal-to-noise ratio (SNR) [7] or channel state information [8].

The proposed algorithm is mathematically inspired by stochastic network optimization framework which is developed under the theory of Lyapunov drift and control [9]–[11]. With this theory, a dynamic control algorithm can be designed for time-average utility optimization (where the utility optimization is defined as WER minimization) subject to queue stability when there exists tradeoff between the utility and stability [10], [12]. This paper presents this dynamic control algorithm and its results about adaptive MIMO detector selection control among soft-input soft-output (SISO) type

M. Choi and J. Moon are with the School of Electrical Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea (emails: {ejaqmf,jmoon}@kaist.ac.kr).

J. Kim is with the School of Computer Science and Engineering, Chung-Ang University, Seoul, Korea (email: joongheon@cau.ac.kr).

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MMSE[1] (SISO-MMSE) [13], SISO-MaxLog and SISO single-tree-search sphere decoding (SISO-STS-SD) [14] algorithms.

The rest of this paper is organized as follows: In §II, two main macro and micro models are described; and the detailed algorithm of main adaptive detector selection algorithm which aims at WER minimization subject to queue stability is described in §III. §IV discusses the performance/complexity tradeoffs in MIMO detectors. The performance of the proposed algorithm is evaluated in §V; and §VI concludes this paper and discusses future research directions.

II. System Models

A. Connected Vehicles Network Model

Consider a vehicular network scenario where a BS group $\mathcal{B}$ consisting of N BSes, b_n where $n \in \{1, \cdots, N\}$, receives the vehicular messages from a large number of vehicles simultaneously as illustrated in Fig. 1. Suppose that each base station is equipped with N_r antennas and only one antenna exists at each vehicle. Since there are many vehicles in the network, it would be difficult to provide orthogonal resources to all wireless links. Therefore, BSes are assumed to take multi-user detection for N_t vehicles. A configurable architecture of BS is assumed to provide a set of K usable detector schemes, $\mathcal{D}$, with D_k, $k \in \{1, \cdots, K\}$, denoting each detector type. Each BS should choose an appropriate detector from $\mathcal{D}$ in order to decode the received signals while avoiding system overload due to heavy load of CAMs and FCD. In Fig. 1, most of the vehicles transmit CAMs to nearby BS. Especially, since upper two lanes are in heavy traffic, the BSes also receive FCD from the vehicles on these lanes to provide the optimal driving path.

The received signal at the n-th BS from N_t vehicles is denoted as follows:

$$\mathbf{y}_n = H_n \mathbf{x}_n + \mathbf{w}_n, \tag{1}$$

where $H_n \in \mathbb{C}^{N_r \times N_t}$ is MIMO wireless channel state information, $\mathbf{x}_n \in \mathbb{C}^{N_t \times 1}$ is the transmitted signal, and $\mathbf{w}_n \in \mathbb{C}^{N_r \times 1}$ is noise. In addition, $\mathbf{w}_n \sim \mathcal{N}(0, \text{diag}\{\sigma_n^2\})$ where σ_n^2 is the noise variance.

B. Receiver Queue Model

In general, queue models have their own arrival and departure processes. When the departures are less frequent than the arrivals, the queue backlog grows. Therefore, achieving higher arrival rates than departure rates is important for stabilizing queues. For each BS $b_n \in \mathcal{B}$, the queue dynamics in each unit time $t \in \{0, 1, \cdots\}$ can be represented as follows:

$$\begin{aligned} Q_n[t+1] &= \max\{Q_n[t] - \mu_n[t], 0\} + \lambda_n[t], &(2)\\ Q_n[0] &= 0 \text{ [Initial Condition of } Q_n[t]], &(3) \end{aligned}$$

where $Q_n[t]$, $\mu_n[t]$, and $\lambda_n[t]$ stand for the queue backlog, the departure and arrival processes of the BS b_n at t, respectively.

In this paper, $\mu_n[t]$ and $\lambda_n[t]$ semantically mean the detected and the received data symbol rates, respectively (Fig. 1). Since $\lambda_n[t]$ relies on the transmission scheme and the channel states, b_n cannot control $\lambda_n[t]$. On the other hand, $\mu_n[t]$ obviously depends on computational complexity of the receiver, because the high-complexity receiver requires longer data processing time, exporting a smaller number of data symbols per second than the low-complexity receivers. Suppose that a unit computation, i.e., floating-point operation (FLOP) [15], spends τ seconds. τ can be considered as the effective processing time per FLOP. Let the receiver which b_n chooses at t requires $c_n[t]$ FLOPs per symbol detection; then the detected data symbol rate can be calculated as $\mu_n[t] = 1/c_n[t]\tau$.

For real-time communications, it is important to avoid the queue overflow while pursuing time-average utility optimization (i.e., maximization of data detection performance). Suppose that the queue is filled with a lot of data blocks (i.e., near overflow). In this case, achieving queue stability should take higher priority than maximization of detection performance. Therefore, a high-speed (i.e., low-complexity) receiver is desired. On the other hand, when the queue is almost empty, the BS prefers to improve the data detection performance. Therefore, the high-complexity receiver which provides the best performance will be selected. In summary, this paper designs a dynamic algorithm which selects a receiver in each unit time which can maximize time-average detection performance (which is equivalent to the minimization of WER) subject to queue stability.

[1]Minimum Mean Squared Error

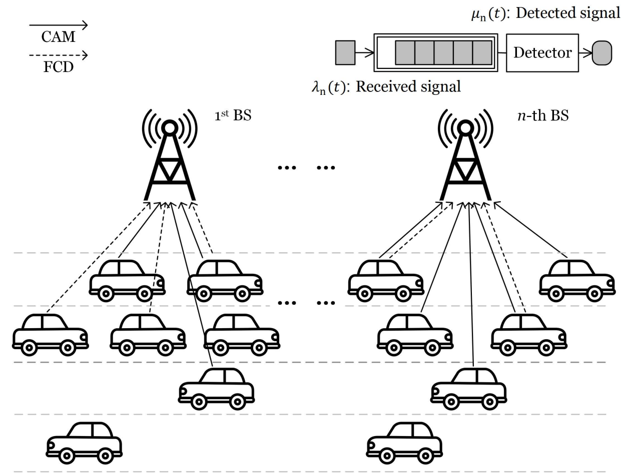

Fig. 1. Connected vehicles environment and the queue model in BS.

III. Queue-Stable Adaptive Detector Selection for Minimizing Word Error Rates

As mentioned above, we focus on adaptive selection of MIMO detectors of different tradeoffs between performance and complexity, based on the configurable detector architecture. While the received symbols are arriving at the queue, the BS should decide which type of the detector will be used for data detection. After the selection, the detector performs data detection and the queue exports the detected data stream. WERs and FLOP are employed as the performance and complexity metrics used in the queue model explained in Sec. II. Based on these metrics, the optimization goal is to find the optimal detector scheme giving the best performance for a BS group $\mathcal{B}$ with subject to queue stability.

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We specifically go after the following minimization problem:

$$\min : \sum_{b_n \in \mathcal{B}} \mathbb{E}\left[\mathcal{E}_n\right] \tag{4}$$

where $\mathcal{E}_n$ is the WER of the detector selected by b_n, $\mathbb{E}\left[\mathcal{E}_n\right]$ stands for the time averaged expected WER as given by

$$\min : \sum_{b_n \in \mathcal{B}} \left(\lim_{t \to \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathcal{E}_n[\tau] \right). \tag{5}$$

Note the objective function has a constraint for queue rate stability, namely,

$$\lim_{t \to \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\left[Q_n[\tau]\right] < \infty, \forall b_n \in \mathcal{B}. \tag{6}$$

Let $\Theta(t)$ denote the column vector of the queue backlogs of all BSes at t, and define the quadratic Lyapunov function $L[t]$ as follows:

$$L[t] = \frac{1}{2}\Theta^{\mathsf{T}}[t]\Theta[t] = \frac{1}{2}\sum_{b_n \in \mathcal{B}} Q_n^2[t], \tag{7}$$

where $\Theta^{\mathsf{T}}[t]$ denotes the transpose of $\Theta[t]$. Then, let $\Delta[t]$ be a conditional quadratic Lyapunov function that can be formulated as $\mathbb{E}[L[t+1] - L[t] | \Theta[t]]$, i.e., the drift on t. The dynamic policy is designed to solve the given optimization formulation by observing the current queue backlog sizes $Q_n[t]$ and determining the receiver selection to minimize a bound on $\mathbb{E}[\mathcal{E}[t]|\Theta[t]] - V\Delta[t]$ [10]. $\mathcal{E}[t]$ is the column vector of $\mathcal{E}_n[t], \forall b_n$ and V is a positive constant of the policy that affects the tradeoff between the performance and delay.

The proposed algorithm involves minimizing a bound on $\mathbb{E}[\mathcal{E}[t]|\Theta[t]] - V\Delta[t]$. This gives the following dynamic algorithm [10] which minimizes

$$\sum_{b_n \in \mathcal{B}} \mathcal{E}_n[t] + V \sum_{b_n \in \mathcal{B}} Q_n[t]\left(\lambda_n[t] - \mu_n[t]\right). \tag{8}$$

The BS cannot control $\lambda_n[t]$ and it is ignored, i.e., (8) is actually updated as follows:

$$\sum_{b_n \in \mathcal{B}} \mathcal{E}_n[t] - V \sum_{b_n \in \mathcal{B}} Q_n[t]\mu_n[t]. \tag{9}$$

In (9), $\mathcal{E}_n[t]$ and $\mu_n[t]$ can be respectively replaced with $\mathcal{E}_n^k[t]$ and $\mu_n^k[t]$ which stand for the WER and the departure process of b_n at t, when b_n chooses $D_k \in \mathcal{D}$ for data detection at t. It is clear that (9) is separable, i.e., each BS b_n minimizes its own objective function. Therefore, (9) can be written as

$$\mathcal{E}_n^k[t] - VQ_n[t]\mu_n^k[t]. \tag{10}$$

By substituting the complexity term for $\mu_n^k[t]$, we can organize our final solution as follows:

$$\arg\min_{D_k \in \mathcal{D}} \left\{ \mathcal{E}_n^k[t] - V\frac{Q_n[t]}{c_n^k[t]\tau} \right\}, \tag{11}$$

controlling the tradeoff between queue stability and WER performance.

However, this optimization process does not guarantee that the stacked queue backlog remains smaller than the actual size of the receiver queue. This is because the constraint (6) only ensures that the queue backlog does not diverge; the queue overflow may occur in practice. Therefore, a procedure to avoid the queue overflow is supplemented by changing V, the weight factor for the term representing complexity. If the queue is almost full, V is increased to weigh the complexity to avoid the queue overflow. On the other hand, the system reduces V in order to allow more backlogs when the queue backlog decreases and there still remains a usable queue margin. The appropriate initial value of V needs to be obtained by experiment because it depends on channel models and queue sizes. In addition, $V \geq 0$ should be satisfied. If $V < 0$, the receiver prefers high-complexity receiver. Moreover, the case with $V = 0$ stands for the situation where queue-stability is not considered any more, and thus the BS chooses its detector only for time-average WER minimization.

Eventually, the proposed algorithm is performed as follows. When V is given, each BS b_n (i) observes the current queue backlog size $Q_n[t]$; (ii) makes the receiver selection according to (11); and (iii) increases or decreases V according to the current queue state. The entire adaptive and dynamic control procedures are described in Algorithm 1. Algorithm 1 can be applied to the adaptive selection of any receiver structures, e.g., MIMO detector, demodulator, or decoder, if the candidates of certain structures are subject to different performance/complexity tradeoffs.

Algorithm 1 Adaptive Detector Selection for Time-Average Minimization of Word Error Rates

Precondition:
- V: parameter for utility-delay tradeoffs
- Q_{max}: maximum allowable queue size
- δ: threshold for preventing the queue overflow
- ΔV: increment/decrement quantity of V

$t = 0$ // T: number of discrete-time operations
while $t \leq T$ **do**
  Observe $Q_n[t]$
  Make detector selection with $\arg\min_{D_k \in \mathcal{D}} \left\{ \mathcal{E}_n^k[t] - V\frac{Q_n[t]}{c_n^k[t]\tau} \right\}$
  if $Q_{max} - \delta < Q_n[t]$ **then** $V = V + \Delta V$
  else if $Q_n[t] < Q_n[t-1]$ **then** $V = V - \Delta V$
  end if
end while

IV. TRADEOFFS IN MIMO DETECTORS

Configurable architectures for MIMO detector [7] [8] which can perform a variety of detection schemes enable the performance/complexity tradeoff to be adjusted. Therefore, we can adaptively select the detector type depending on the current queue state based on configurable architecture. In addition, when a certain detector has a parameter that controls the tradeoff, Algorithm 1 conducts decision-making for parameter control in order to achieve queue stabilization. Three types of MIMO detectors are considered: SISO-MMSE [13], SISO-MaxLog, and SISO-STS-SD [14], under the consideration of turbo equalization receiver structure.

SISO-STS-SD [14] is based on single-tree-search, and the number of visited nodes in the tree searching process is the dominant factor of its complexity. In SISO-STS-SD, an LLR

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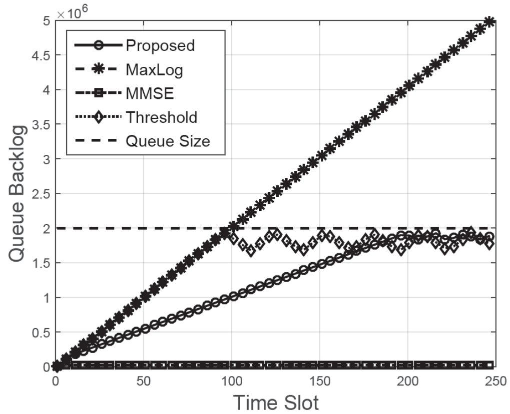

Fig. 2. Queue backlog variation plots versus time slot.

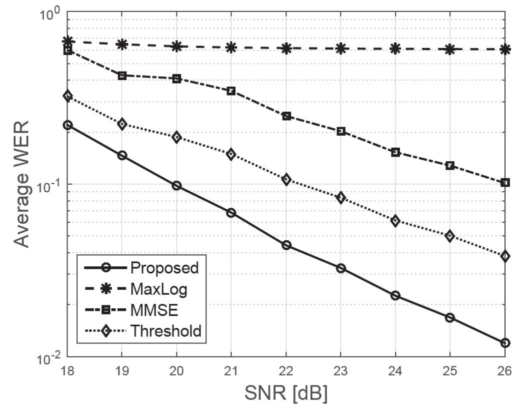

Fig. 3. Average WER performance plots versus SNR.

clipping parameter controls the performance/complexity trade-off. In this case, a larger parameter value gives a better error rate, but induces visits to a larger number of the nodes in the sphere decoding tree [14]. A finite value of the LLR clipping parameter helps to prune some sub-trees in the process of tree searching, and eventually results in a smaller number of node visits. In other words, a smaller LLR clipping parameter makes SISO-STS-SD require less computations for decoding at the expense of performance a bit. Hereafter, for brevity, the detector candidates will be called MMSE, MaxLog, and SD_i, respectively, where i indicates the LLR clipping parameter. In SD, four different LLR clipping parameters are considered for simulation, i.e., $i = 4, 6, 8, 16$. Therefore, six detector types are under consideration as summarized in Table. I.

A. Performance Metric

The WER is one of the best choices for the performance metric in practical scenarios with a fixed SNR. We obtained the WERs of the MIMO detectors via data-intensive Monte Carlo simulations. Based on turbo equalization structure, a flat fading MIMO channel with $N_t = 2$ and $N_r = 2$, 16-QAM, a 1/2-rate [7 5] convolutional code and a random interleaver are considered. The BS can expect WERs based on channel statistics by conducting data-intensive simulations, so the expected WERs according to received SNRs are pre-stored as a type of codebook.

B. Complexity Metric

As the complexity metric, FLOP is employed. FLOP is a common measure for any computer working in real-time applications [15], and it can be a good measurement index for the processing time. The number of FLOPs is also directly related to actual time latency. Each floating operation requires a floating-point register, and therefore it is also associated with the hardware size. This paper supposes that a complex summation requires a single FLOP and a complex multiplication requires 3 FLOPs. The number of FLOPs required for other arithmetic operations can be found in [16].

The number of FLOPs required for the MMSE and MaxLog detectors does not change with channel variations. The matrix computations, matrix inversion, and soft LLR computations are major factors in determining the FLOPs of MMSE and MaxLog. On the other hand, complexity of the sphere detector varies with the different channel gains and SNR values due to the fact that the number of visited nodes in the tree searching algorithm depends on the randomness of the signal and noise. Therefore, FLOPs of the sphere detector should be computed empirically for a given SNR. FLOP in this case usually depends on the node processing and the soft LLR computations. Table I shows how much FLOPs are required for each detector at a 26dB of SNR.

V. Performance Evaluation

For evaluating the performance of the proposed algorithm via data-intensive simulations, the initial settings of $\lambda_n[t]$, Q_{max}, V, ΔV and τ are determined as follows. We first suppose $\lambda_n[t]$ is a fixed symbol rate. According to the LTE specifications, a resource block in LTE downlink includes 12 symbols and its time slot is 5 ms. Thus $\lambda_n[t]$ becomes 24000 symbols per second. In addition, we assume that $\tau = 3 \times 10^{-8}$ sec/FLOP and that initially $V = 10^{-11}$, $\Delta V = 10^{-12}$, $Q_{max} = 2 \times 10^6$, and $\delta = 10^5$. In practice, τ and Q_{max} are determined according to the system architecture; then V, ΔV, and δ can be properly selected. Especially, when the system requires low latency or low complexity, large V will be appropriate because V acts as a weight on complexity.

In order to verify the performance of the proposed algorithm, three comparison cases are considered in this paper:

- MMSE only: The BSes perform only MMSE.
- MaxLog only: The BSes perform only MaxLog. If queue overflow occurs, WER becomes 1.
- Threshold: First, the BSes perform MaxLog which provides the best performance. When the queue is near full, MMSE is used to empty the queue sufficiently, and then MaxLog is employed again after reducing the queue backlog. These steps are repeated.

The first two cases are extreme, and the last one is a compromise which sets a limit for the stacked queue backlog. The queue backlog plots versus time t at SNR=26 dB are presented in Fig. 2. When only MMSE is performed, the queue backlog is not stacked at all and when only MaxLog is

TABLE I
FLOP AND NUMBER OF USES FOR MIMO DETECTORS AT SNR=26 DB

Detector	MMSE	SD_4	SD_6	SD_8	SD_{16}	MaxLog
FLOP	814	1876.7	1920.3	2005.6	2262.6	8947.6
Uses	19	0	0	3	220	8

performed, the queue backlog continues to accumulate over time. It is easily expected that these two cases would not give good error rate performances due to the fact that the MMSE has the worst performance and MaxLog causes the queue overflow. The 'threshold' case avoids overflow; there is the oscillating tendency after approaching the maximum value of available queue backlog. The proposed algorithm shows the similar tendency in queue backlog management to that of the threshold case, however it slowly converges to maximum queue backlog. The reason is that the threshold only scheme performs MaxLog until the queue is almost full, red whereas the proposed algorithm adaptively chooses MaxLog and SD_i to minimize the time-average WER.

The average WER plots versus SNR are shown in Fig. 3. If only MaxLog is performed, the queue overflow occurs after some time, and it is true that error rates become meaningless. However, other cases do not allow overflow and the proposed algorithm shows the best average WER performance among them. As observed in Fig. 2, it is obvious that the average WER performance is minimized by adjusting the rate at which the queue backlog approaches the maximum queue-backlog.

Table I also shows the numbers of uses for the detectors. SD_{16} is the most frequently used, and MMSE, SD_8, and MaxLog are chosen a few times. However, SD_4 and SD_6 are not selected at all. We can say that performance gains of SD_4 and SD_6 over MMSE are not enough to replace MMSE, because of increased complexity. It can be also said that it is better to use SD_8 that provides a much better performance, rather than choosing SD_4 and SD_6, if it is allowable to increase the complexity a bit. Thus, SD_4 and SD_6 are not needed for a BS group in this environment, and it is clear that the proposed algorithm is able to decide which receiver type would be useful for a certain system environment.

VI. CONCLUSIONS AND FUTURE WORK

This paper proposes the dynamic control algorithm for adaptive detector selection under the constraint of queue stabilization in low-latency infrastructure-to-vehicle (V2X) communications. By incorporating computational complexity of the detectors into the receiver queue model at V2X base stations, the proposed method provides improved decoder selection decision making for the BSes of connected vehicles environments to select one of the candidate detector schemes so as to prevent unwanted delay, possibly at the expense of degraded performance depending on queue-backlog information. The proposed algorithm basically pursues time-averaged detector word error rate minimization under the constraint of queue stabilization which actively controls performance-complexity tradeoffs.

As a future research direction, it is considerable to utilize coordinated multi-point (CoMP) [17] and cloud radio access networks (CRAN) [18] based advanced communication technologies which can be beneficial for improving the performance of the proposed adaptive detector selection algorithm by allowing the collaboration among BSes with centralized computing resources.

ACKNOWLEDGEMENT

This work was supported by National Research Foundation of Korea under Grant 2016R1C1B1015406. J. Moon and J. Kim are corresponding authors of this paper.

REFERENCES

[1] S. Lee, S. Hyeon, J. Kim, H. Roh, and W. Lee, "The Useful Impact of Carrier Aggregation: A Measurement Study in South Korea for Commercial LTE-Advanced Networks," *IEEE Vehicular Technol. Magazine*, 12(1):55–62, Mar. 2017.
[2] G. Araniti, C. Campolo, M. Condoluci, A. Iera, and A. Molinaro, "LTE for Vehicular Networking: A Survey," *IEEE Communi. Magazine*, 51(5):148–157, May 2013.
[3] J. Kim, S.-C. Kwon, and G. Choi, "Performance of Video Streaming in Infrastructure-to-Vehicle Telematic Platforms With 60-GHz Radiation and IEEE 802.11ad Baseband," *IEEE Trans. Vehicular Technol.*, 65(12):10111–10115, Dec. 2016.
[4] X. Cheng, Q. Yao, M. Wen, C. X. Wang, L. Y. Song and B. L. Jiao, "Wideband Channel Modeling and Intercarrier Interference Cancellation for Vehicle-to-Vehicle Communication Systems," *IEEE J. on Selected Areas in Communications*, 31(9):434–448, Sept. 2013.
[5] X. Cheng, M. Wen, L. Yang and Y. Li, "Index Modulated OFDM with Interleaved Grouping for V2X Communications," in *Proc. IEEE Int'l Conf. Intelligent Transportation Systems (ITSC)*, 2014.
[6] C. Windpassinger, L. Lampe, R. F. H. Fischer, and T. Hehn, "A Performance Study of MIMO Detectors," *IEEE Trans. Wireless Communications*, 5(8):2004–2008, Aug. 2006.
[7] E. P. Adeva, T. Seifert, and G. Fettweis, "VLSI Architecture for MIMO Soft-Input Soft-Output Sphere Detection," *J. Signal Processing Systems*, 70(2):125–143, Feb. 2013.
[8] F. Sheikh, C.-H. Chen, D. Yoon, B. Alexandrov, K. Bowman, A. Chun, H. Alavi, and Z. Zhang, "3.2 Gbps Channel-Adaptive Configurable MIMO Detector for Multi-Mode Wireless Communication," *J. Signal Processing Systems*, 84(3):295–307, Stept. 2016.
[9] L. Tassiulas and A. Ephremides, "Stability Properties of Constrained Queueing Systems and Scheduling Policies for Maximum Throughput in Multihop Radio Networks," *IEEE Trans. Automatic Control*, 37(12):1936–1948, Dec. 1992.
[10] J. Kim, G. Caire, and A. F. Molisch, "Quality-Aware Streaming and Scheduling for Device-to-Device Video Delivery," *IEEE/ACM Trans. Networking*, 24(4):2319–2331, Aug. 2016.
[11] J. Kim and W. Lee, "Stochastic Decision Making for Adaptive Crowdsourcing in Medical Big-Data Platforms," *IEEE Trans. Systems, Man, and Cybernetics: Systems*, 45(11):1471–1476, Nov. 2015.
[12] D. Bethanabhotla, G. Caire, and M. J. Neely, "Adaptive Video Streaming for Wireless Networks With Multiple Users and Helpers," *IEEE Trans. Communications*, 63(1):268–285, Jan. 2015.
[13] M. Tuchler, A. C. Singer, and R. Koetter, "Minimum Mean Squared Error Equalization using a Priori Information," *IEEE Trans. Signal Processing*, 50(3):673–683, Mar. 2002.
[14] C. Studer, A. Burg, and H. Bölcskei, "Soft-Output Sphere Decoding: Algorithms and VLSI Implementation," *IEEE J. Selected Areas in Communications (JSAC)*, 26(2):290-300, Feb. 2008.
[15] R. Hunger, *Floating Point Operations in Matrix-Vector Calculus*, Munich University of Technology, 2005.
[16] A. M. Elshokry, *Complexity and Performance Evaluation of Detection Schemes for Spatial Multiplexing MIMO Systems*, Ph.D. Dissertation, Islamic University Gaza, 2010.
[17] K. Kwak, H. W. Je, S. H. Park, and S. Choi, "CoMP Joint Transmission for Gaussian Broadcast Channels in Delay-Limited Networks," *IEEE Trans. Vehicular Technol.*, 66(3):2053–2058, Mar. 2017.
[18] X. Huang, G. Xue, R. Yu, and S. Leng, "Joint Scheduling and Beamforming Coordination in Cloud Radio Access Networks With QoS Guarantees," *IEEE Trans. Vehicular Technol.*, 65(7):5449–5460, Jul. 2016.