Impact of Quantized Side Information on Subchannel Scheduling for Cellular V2X

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Contents

Figure 1: Connected world

Background

- 3GPP[1] proposed in Release 14, two novel schemes to support sidelink vehicular communications
  - C-V2X *mode-3* (centralized)
  - C-V2X[2] *mode-4* (distributed)

[1] 3GPP: The 3rd Generation Partnership Project
[2] C-V2X: Cellular Vehicle–to–Everything
[3] D2D: Device–to–Device communications

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  - C-V2X *mode-3* (centralized)
  - C-V2X[2] *mode-4* (distributed)

- C-V2X *modes* are based on LTE-D2D[3] technology, where similar communication modalities were proposed.

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- 3GPP[1] proposed in Release 14, two novel schemes to support sidelink vehicular communications
  - C-V2X *mode-3* (centralized)
  - C-V2X[2] *mode-4* (distributed)
- C-V2X *modes* are based on LTE-D2D[3] technology, where similar communication modalities were proposed.
- However, in LTE-D2D (introduced for public safety) the ultimate objective is to reduce energy consumption (at the expense of compromising latency).

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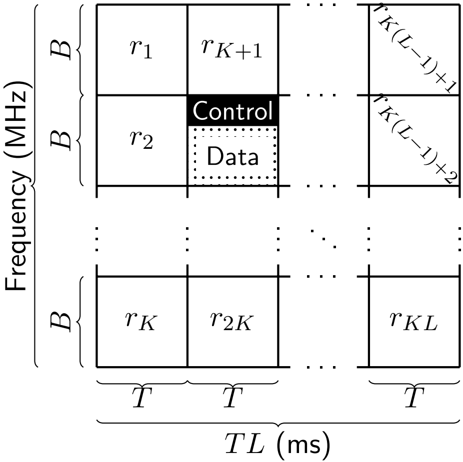
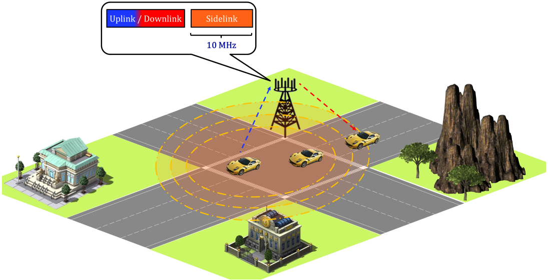
Sidelink Subchannels



- T: duration of a subframe
- K: number of subchannels per subframe
- L: total number of subframes for allocation
- B: subchannel bandwidth

C-V2X Mode 3

- Besides **uplink** and **downlink** (Uu), vehicles can also communicate via **sidelink** (PC5), which supports direct communications between vehicles.



Identified Problems

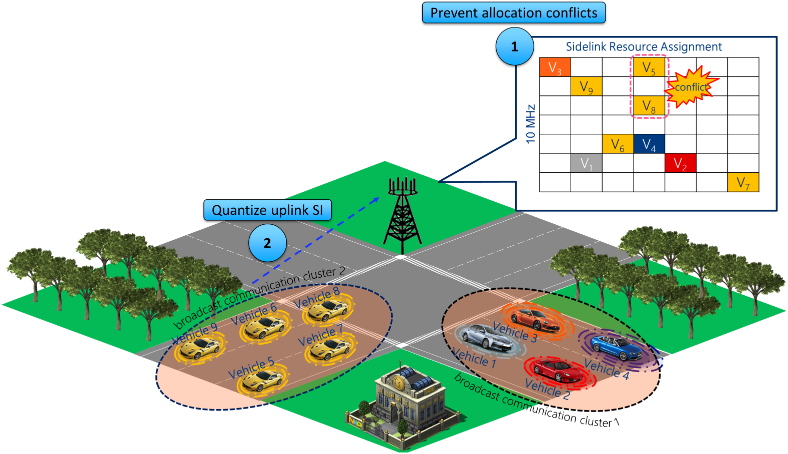


Figure 2: Vehicular clusters

Optimization Problem

The subchannel allocation problem can be expressed as:

$$\max \ \mathbf{c}^T \mathbf{x} \tag{1a}$$

$$\text{subject to} \ \left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}} \right] \otimes \mathbf{1}_{1\times K} \ \mathbf{x} = \mathbf{1} \tag{1b}$$

Note: For completeness, we have assumed that the number of vehicles is equal to the number of subframes, i.e. $N = L$

This problem cannot be approached by known matching algorithms. So we proceed as follows

Properties

Property 1 (Product of two tensor products)
Let $\mathbf{X} \in \mathbb{R}^{m \times n}$, $\mathbf{Y} \in \mathbb{R}^{r \times s}$, $\mathbf{W} \in \mathbb{R}^{n \times p}$, and $\mathbf{Z} \in \mathbb{R}^{s \times t}$, then

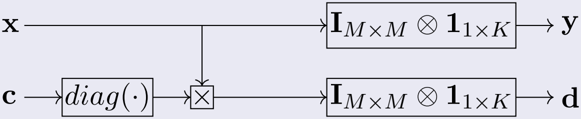
$$\mathbf{XY} \otimes \mathbf{WZ} = (\mathbf{X} \otimes \mathbf{W})(\mathbf{Y} \otimes \mathbf{Z}) \in \mathbb{R}^{mr \times pt}$$

Property 2 (Pseudo-inverse of a tensor product)
Let $\mathbf{X} \in \mathbb{R}^{m \times n}$ and $\mathbf{Y} \in \mathbb{R}^{r \times s}$, then

$$(\mathbf{X} \otimes \mathbf{Y})^{\dagger} = \mathbf{X}^{\dagger} \otimes \mathbf{Y}^{\dagger} \in \mathbb{R}^{ns \times mr}$$

Resultant Optimization Problem

Transformation



$$\mathbf{d} = \lim_{\beta \to \infty} \frac{1}{\beta} \overset{\circ}{\log}\left\{ (\mathbf{I}_{M \times M} \otimes \mathbf{1}_{1 \times K}) \mathrm{e}^{\circ \beta \mathbf{c}} \right\}$$

$\overset{\circ}{\log}\{\cdot\}$: Element-wise natural logarithm.
$\mathrm{e}^{\circ\{\cdot\}}$ Hadamard exponential.

Resultant Optimization Problem

Original Problem

$$\max\ \mathbf{c}^T\mathbf{x},\quad \text{subject to} \begin{bmatrix} \mathbf{I}_{N\times N}\otimes \mathbf{1}_{1\times N} \\ \hline \mathbf{1}_{1\times N}\otimes \mathbf{I}_{N\times N} \end{bmatrix} \otimes \mathbf{1}_{1\times K}\ \mathbf{x} = \mathbf{1}$$

Resultant Problem

$$\max\ \mathbf{d}^T\mathbf{y},\qquad \text{subject to} \begin{bmatrix} \mathbf{I}_{N\times N}\otimes \mathbf{1}_{1\times N} \\ \hline \mathbf{1}_{1\times N}\otimes \mathbf{I}_{N\times N} \end{bmatrix}\mathbf{y} = \mathbf{1}.$$

where $\mathbf{d} = (\mathbf{I}_{M\times M}\otimes \mathbf{1}_{1\times K})diag(\mathbf{c})\mathbf{x}$ and $\mathbf{y} = (\mathbf{I}_{M\times M}\otimes \mathbf{1}_{1\times K})\mathbf{x}$

Dimensionality reduction: $\rightarrow |\mathbf{x}| = MK \qquad \rightarrow |\mathbf{y}| = M.$

The resultant problem can now be approached through the Kuhn-Munkres Algorithm.

Quantization of Uplink Side Information

- Transmission of side information via uplink in order for the eNodeBs to perform scheduling is crucial in the proposed approach.
- Thus, the impact of quantization on the uplink side information has to be assessed.
- A suitable degree of granularity should not degrade severely the optimal scheduling.

Simulation Scenario

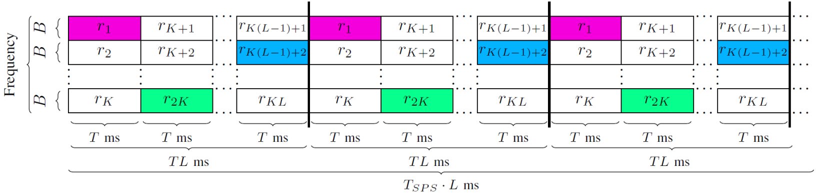


Figure 3: Semi-Persistent Subchannel Reservation

Simulation Scenario

Consider the following setting:

- Subchannel length: 1 ms
- Subchannels width: 1.26 MHz (7 RBs)
- CAM message rate: 10 Hz
- Scheduling solutions:
  - Proposed approach (graph-based)
  - Greedy approach
  - Random approach
- Levels of granularity:
  - 4 bits
  - 3 bits
  - 2 bits

CDF of Proposed Approach

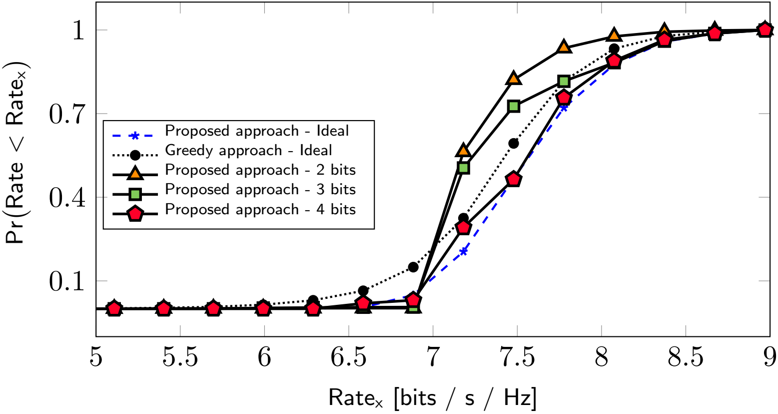


Figure 4: CDF function for the proposed approach

CDF of Greedy Approach

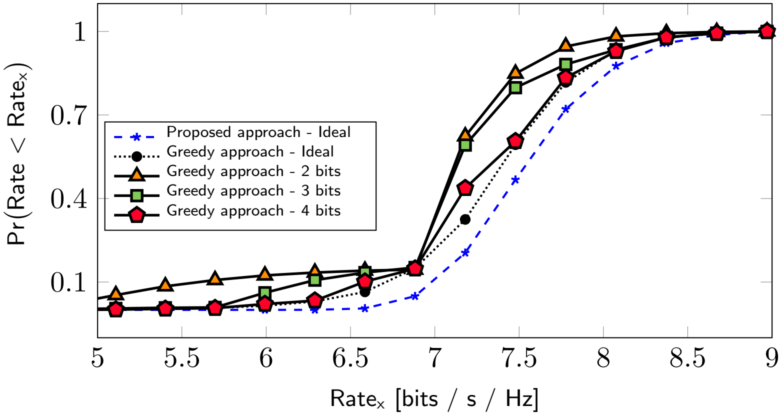


Figure 5: CDF function for greedy algorithm

Scenario: System Performance Using 3 Bits

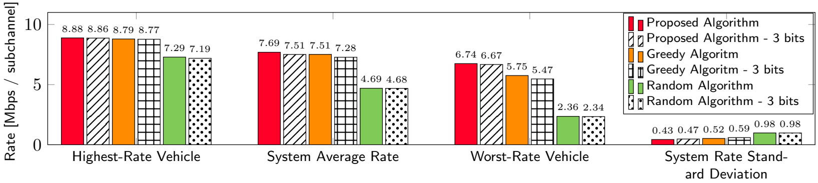


Figure 6: Vehicles data rate: performance comparison between fine-grained vs 3-bit quantization ($N = 100$)

Scenario: System Performance Using 2 Bits

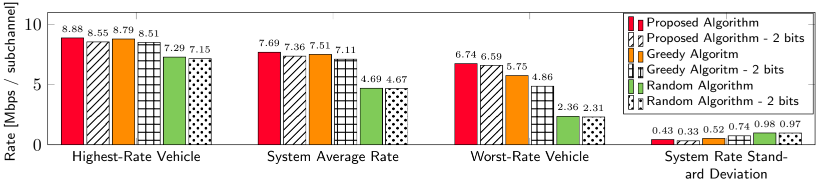


Figure 7: Vehicles data rate: performance comparison between fine-grained vs 2-bit quantization $(N = 100)$

Scenario: Least-Favored Vehicle (2 bits)

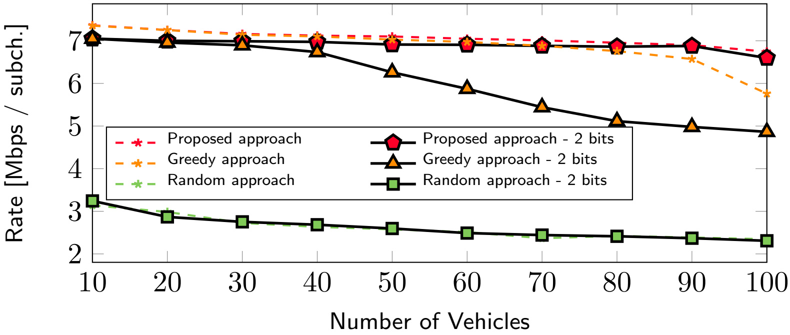


Figure 8: Worst-rate vehicle (2 bits)

Scenario: Least-Favored Vehicle (3 bits)

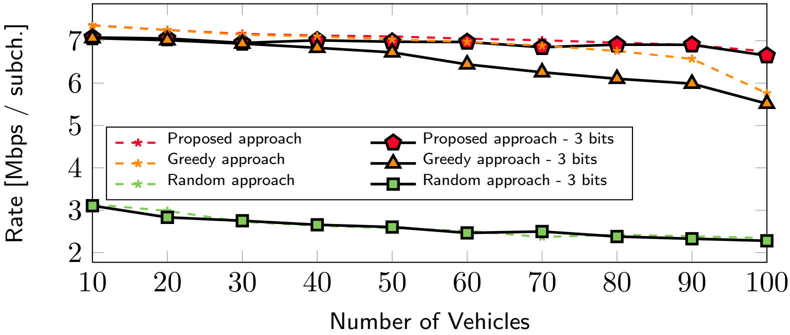


Figure 9: Worst-rate vehicle (3 bits)

Scenario: Least-Favored Vehicle (4 bits)

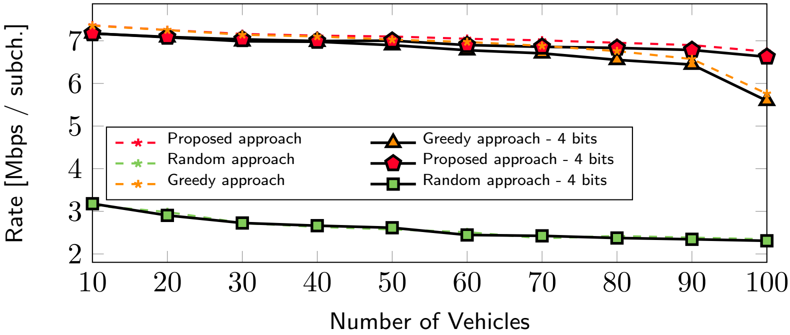


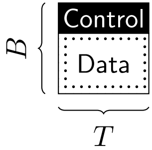
Figure 10: Worst-rate vehicle (4 bits)

Conclusions

- We presented a subchannel assignment approach for V2V *mode-3* based on weighted bipartite graph matching considering constraints to prevent intra-cluster conflicts.
- The proposed approach is compared against greedy and random algorithms.
- The three approaches were assessed using both fine-grained and quantized SINR values.
- When either the proposed approach or greedy approach are used, 3 quantization bits are enough in order not to deviate notoriously from the ideal fine-grained curve performance.

Questions

Subchannel Structure



Assuming a 10 MHz ITS (Intelligent Transportation Systems) channel, up to 7 subchannels per subframe can be obtained. Thus,

- B: 1.26 MHz
- T: 1 ms (2 slots of 0.5 ms each)
- Control: 2 RBs[4] per slot ← 24 subcarriers
- Data: 5 RBs per slot ← 60 subcarriers

Subchannel

A subchannel of 7 RBs is capable of transporting a basic CAM message with a payload of 200 bytes.

[4]RB: A resource block consits of 12 subcarriers

Optimization Problem

Objective Function

$\max \ \mathbf{c}^T\mathbf{x}$

Because $\mathbf{x} \in \mathbb{B}^{MK}$, then the objective function can be recast as

$$\mathbf{c}^T\mathbf{x} \equiv \mathbf{x}^T diag(\mathbf{c})\mathbf{x}$$

without affecting optimality.

Note that $M = N^2$.

Optimization Problem

Objective Function

$\max \, \mathbf{c}^T \mathbf{x}$

For any vehicle v_i,

$$x_{ij} x_{ik} = 0, \; r_j, r_k \in \mathcal{R}_\alpha.$$

Moreover,

$$c_{ij} x_{ij} x_{ik} = 0, \; r_j, r_k \in \mathcal{R}_\alpha.$$

In general, for N vehicles

$$\mathbf{x}^T \left(\mathbf{I}_{M \times M} \otimes [\mathbf{1}_{K \times K} - \mathbf{I}_{K \times K}] \right) diag(\mathbf{c}) \mathbf{x} = 0.$$

Optimization Problem

Objective Function

$\max \ \mathbf{c}^T\mathbf{x}$

As long as $\mathbf{x}^T\left(\mathbf{I}_{M\times M}\otimes[\mathbf{1}_{K\times K}-\mathbf{I}_{K\times K}]\right)diag(\mathbf{c})\mathbf{x}=0$ holds, conflicts will be prevented.

We can aggregate this condition to the objective function. Hence,

$$\mathbf{c}^T\mathbf{x}=\mathbf{x}^T diag(\mathbf{c})\mathbf{x}+\mathbf{x}^T\left(\mathbf{I}_{M\times M}\otimes[\mathbf{1}_{K\times K}-\mathbf{I}_{K\times K}]\right)diag(\mathbf{c})\mathbf{x}$$

Further manipulation leads to

$$\mathbf{c}^T\mathbf{x}=\mathbf{x}^T(\mathbf{I}_{M\times M}\otimes\mathbf{1}_{K\times K})diag(\mathbf{c})\mathbf{x}$$

Optimization Problem

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Property 1 (Product of two tensor products)
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$$\mathbf{XY} \otimes \mathbf{WZ} = (\mathbf{X} \otimes \mathbf{W})(\mathbf{Y} \otimes \mathbf{Z}) \in \mathbb{R}^{mr\times pt}$$

$$\begin{aligned}
\mathbf{c}^T\mathbf{x} &= \mathbf{x}^T(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times K})diag(\mathbf{c})\mathbf{x} \\
&= \mathbf{x}^T(\mathbf{I}_{M\times M}\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times 1}\mathbf{1}_{1\times K})diag(\mathbf{c})\mathbf{x} \\
&= \underbrace{\mathbf{x}^T(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times 1})}_{\mathbf{y}^T}\underbrace{(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{1\times K})diag(\mathbf{c})\mathbf{x}}_{\mathbf{d}}
\end{aligned}$$

Optimization Problem

Constraints

$$\text{subject to} \left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right] \otimes \mathbf{1}_{1\times K}\ \mathbf{x} = \mathbf{1}$$

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Optimization Problem

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$$\left(\left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right] \otimes \mathbf{1}_{1\times K}\right)\left(\mathbf{I}_{M\times M} \otimes \mathbf{1}^{\dagger}_{1\times K}\right)\mathbf{y} = \mathbf{1}$$

$$= \left(\left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right] \mathbf{I}_{M\times M}\right) \otimes \underbrace{\left(\mathbf{1}_{1\times K}\mathbf{1}^{\dagger}_{1\times K}\right)}_{1} \mathbf{y} = \mathbf{1}$$

$$= \left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right] \mathbf{y} = \mathbf{1}$$