Deep Learning Based 5G mm-Wave beamforming management scheme

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Overview

Introduction

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Figure 1: Ever-growing internet services.

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Figure 2: 5G mobile network.

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- In 5G mm-Wave the beamforming technique was introduced for achieve the best SNR through the set of operations known as beam management

Problem statements and Research objective

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Research objective

The objective is to propose a beamforming management (with centralized architecture) mechanism in the context of dense mm-Wave networks by using deep learning.

Mobile network concepts

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mm-Wave, MIMO, massive MIMO

- mm-Wave : Radio waves covering frequences from 30-300Ghz
- MIMO : Multiple Imput Multiple Output
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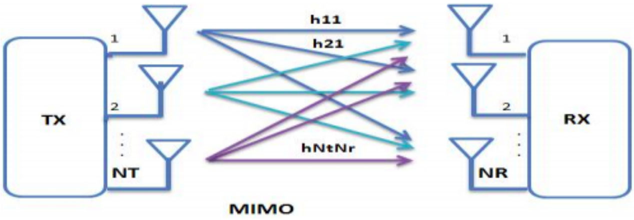

Figure 3: MIMO System.

Mobile network concepts

$$H = \begin{pmatrix} h_{11} & h_{12} & \dots & h_{1N_t} \\ h_{21} & h_{22} & h_{23} & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ h_{N_r1} & h_{N_r2} & \dots & h_{N_rN_t} \end{pmatrix} \tag{1}$$

MIMO signal can be defined by:

$$Y = HX + n \tag{2}$$

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Antenna selection

- process to select the suitable beam from transmitter With the perfect knowledge of the channel characteristic
- selection is based on Signal to Noise Ratio (SNR) at each receive antenna.

Mobile network concepts

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Signal processing techniques used in sensor array for directional signal transmission or reception

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Figure 4: MIMO and Beamforming

Artificial intelligence concepts and methods

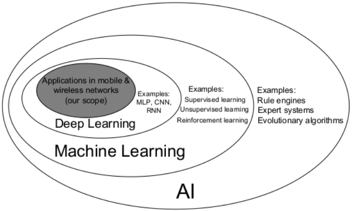
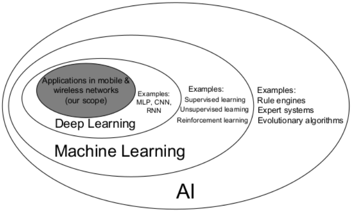


Figure 5: Venn diagram for AI, ML, DL



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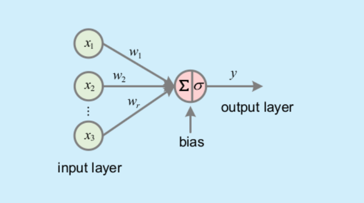
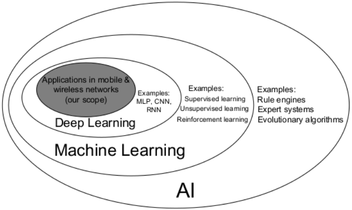


(a) Mathematical model of neuron or perceptron

Artificial intelligence concepts and methods



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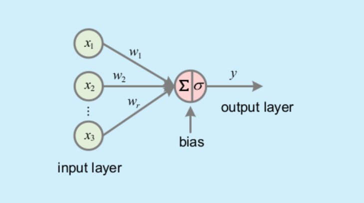
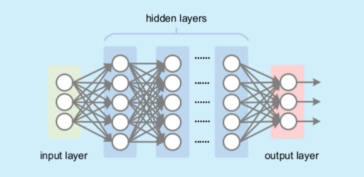


(a) Mathematical model of neuron or perceptron



(b) A fully connected feed forward NN architecture

Deep Learning Algorithms

- Deep Neural Network (DNN)
- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)
- Long Short Term Memory (LSTM) etc...

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$$\sigma = max(0, x) \tag{4}$$

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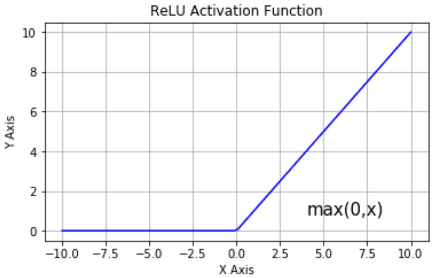

Figure 7: ReLU Activation Function.

System model

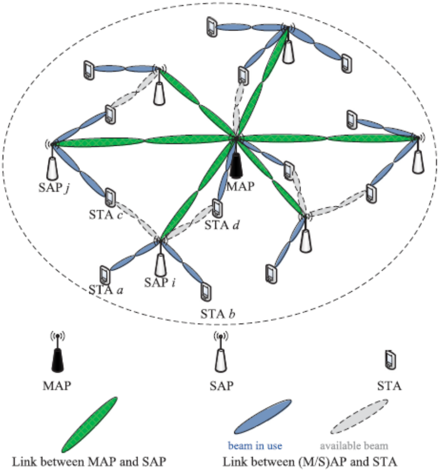

Figure 8: Dense mm-Wave network architecture.

Beamforming Training(BFT) mechanism

$$G(\alpha, \theta) = \begin{cases} \frac{2\pi - (2\pi - \alpha)\epsilon}{\alpha} & \text{if } |\theta| \leq \frac{\alpha}{2}, \\ \epsilon & \text{Otherwise} . \end{cases} \tag{5}$$

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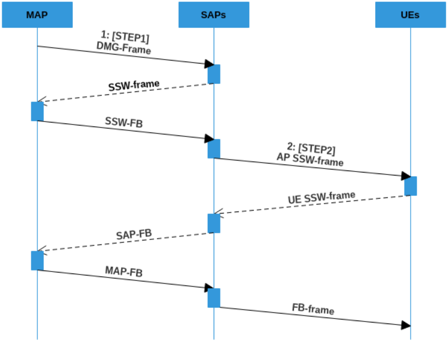

Figure 9: BFT mechanism in dense mm-Wave.

BFT Mechanism and Problem formulation

$$b_{ad/ay} = (b_{AP} + n.b_{AP} + n) + (b_{AP} + s.b_{STA} + s).(n+1) \quad (6)$$

$$b_{pro} = (b_{AP} + n.b_{AP} + n) + b_{AP}.(n+1) + s.(b_{STA} + 2n + 1) \quad (7)$$

$$b_{save} = b_{ad/ay} - b_{pro} = s.n.(b_{STA} - 1) \quad (8)$$

$$b_{AP} = \frac{2\pi}{\alpha_{AP}} \qquad b_{STA} = \frac{2\pi}{\alpha_{STA}}$$

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Directional transmit gain $G^t_{i,j}$ and directional received gain $G^r_{i,j}$ in In the dense mm-Wave network:

$$G^t_{i,j} = \frac{2\pi - (2\pi - \alpha^t_{i,j})\epsilon}{\alpha^t_{i,j}} \quad (9)$$

Problem formulation

$$G_{i,j}^{r} = \frac{2\pi - (2\pi - \alpha_{i,j}^{r})\epsilon}{\alpha_{i,j}^{r}}, \quad (10)$$

$$h_{i,j}(\tau) = \sum_{k=1}^{K} \overset{(\mathrm{k})}{G_{i,j}^{t}} \overset{(\mathrm{k})}{G_{i,j}^{r}} \overset{(\mathrm{k})}{\chi_{i,j}^{c}} \, \delta(\tau - \overset{(\mathrm{k})}{\tau_{i,j}}), \quad (11)$$

$$\overset{(\mathrm{k})}{G_{i,j}^{c}} = |\overset{(\mathrm{k})}{\chi_{i,j}^{c}} \, \delta(\tau - \overset{(\mathrm{k})}{\tau_{i,j}})|^{2}, \quad (12)$$

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Problem formulation

$$P^r_{i,j} = P^t_{i,j} \sum_{k=1}^{K} G^{t}_{i,j}{}^{(k)} G^{r}_{i,j}{}^{(k)} G^{c}_{i,j}{}^{(k)}, \tag{14}$$

$$P^I_{a,b\to i,j} = P^t_{i,j} \sum_{k=1}^{K} G^{t}_{a,b\to i,j}{}^{(k)} G^{r}_{a,b\to i,j}{}^{(k)} G^{c}_{i,b}{}^{(k)}, \tag{15}$$

$$SINR_{i,j} = \frac{x_{i,j} P^r_{i,j}}{\sum_{a\in\mathbb{S}\setminus i} \sum_{b\in\mathbb{N}\setminus j)} x_{a,b} P^I_{a,b\to i,j} + W.N_0} \tag{16}$$

$$Score = \frac{C_1 * level + C_2 * Skill}{\sum(C_1 + C_2)} \quad (17)$$

Problem formulation

Problem formulation

$$
\begin{aligned}
&P_1 : \underset{X,P,A}{\text{Maximize}} \sum_{i\in\mathbb{S}} \sum_{j\in\mathbb{N}} x_{i,j} W log_2(1 + SINR_{i,j})\\
&\text{subject to :}\\
&C_1 : x_{i,j} = \{0,1\}, \forall i \in \mathbb{S}, j \in \mathbb{N},\\
&C_2 : \sum_{j\in\mathbb{N}} x_{i,j} \leq 1, \forall i \in \mathbb{S},\\
&C_3 : \sum_{i\in\mathbb{S}} x_{i,j} \leq b_{AP}, \forall j \in \mathbb{N},\\
&C_4 : \sum_{i\in\mathbb{S}} x_{i,j} P_{i,j} \leq p_j^{max}, \forall j \in \mathbb{N},\\
&C_5 : \alpha^{min} \leq \alpha_{i,j} \leq \alpha^{max}, \forall i \in \mathbb{S}, j \in \mathbb{N},\\
&C_6 : \sum_{i\in\mathbb{S}} x_{i,j}\alpha_{i,j} \leq 2\pi, \forall j \in \mathbb{N},
\end{aligned}
\tag{18}
$$

Problem formulation

Problem formulation

$$
\begin{aligned}
&P_2 : \underset{X,P,A}{\text{Maximize}} \sum_{i\in\mathbb{S}} \sum_{j\in\mathbb{N}} x_{i,j} W log_2(1 + SINR_{i,j}) \\
&\text{subject to :} \\
&C_1 : x_{i,j} = \{0,1\}, \forall i \in \mathbb{S}_j, j \in \mathbb{N}, \\
&C_2 : \sum_{j\in\mathbb{N}} x_{i,j} \leq 1, \forall i \in \mathbb{S}, \\
&C_3 : \sum_{i\in\mathbb{S}_j} x_{i,j} \leq b_{AP}, \forall j \in \mathbb{N}, \\
&C_4 : \sum_{i\in\mathbb{S}_j} x_{i,j} P_{i,j} \leq p_j^{max}, \forall j \in \mathbb{N}, \\
&C_5 : \alpha^{min} \leq \alpha_{i,j} \leq \alpha^{max}, \forall i \in \mathbb{S}_j, j \in \mathbb{N}, \\
&C_6 : \sum_{i\in\mathbb{S}_j} x_{i,j}\alpha_{i,j} \leq 2\pi, \forall j \in \mathbb{N},
\end{aligned}
\tag{19}
$$

Proposed approach solution

Block coordinate descent method

1. Initialize P and A to obtain the optimized X^*;
2. Use the optimized X^* and initialized P to get the optimized A^*;
3. Use the optimized X^* and A^* to find the optimized P^*.

Linear sub-assignment problems (LSAP)

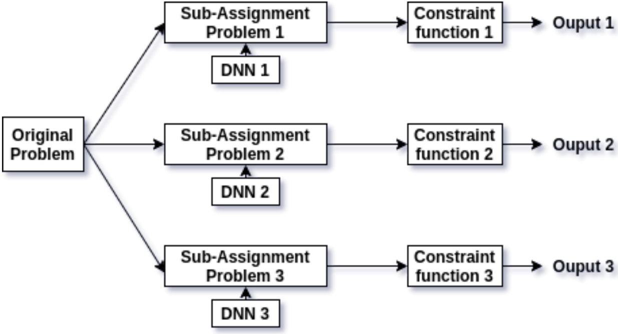


Figure 10: System model of DNN based LSAP

Fully connected neural network

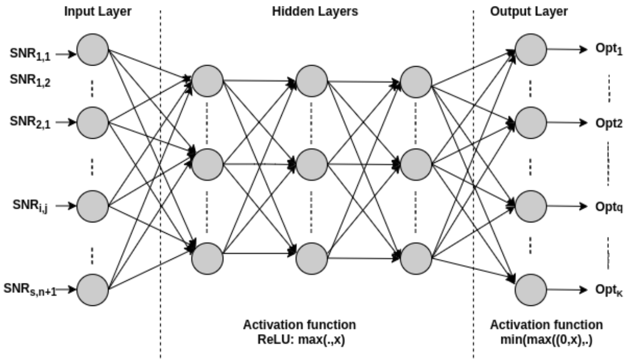
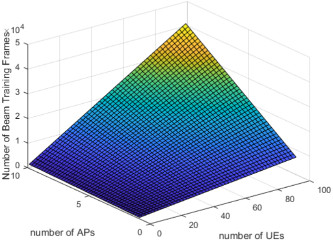
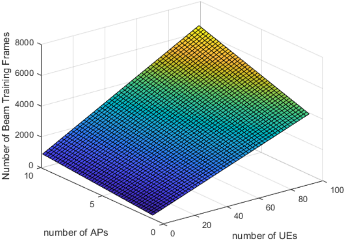


Figure 11: DNN structure for j-th sub-assignment problem.

BFT: Impact of the number of *AP* and *STA*/UEs



(a) The overhead of IEEE802.11ad/ay BFT.



(b) The overhead of proposed BFT mechanism.

BFT: Impact of the number of *AP* and *STA*/UEs

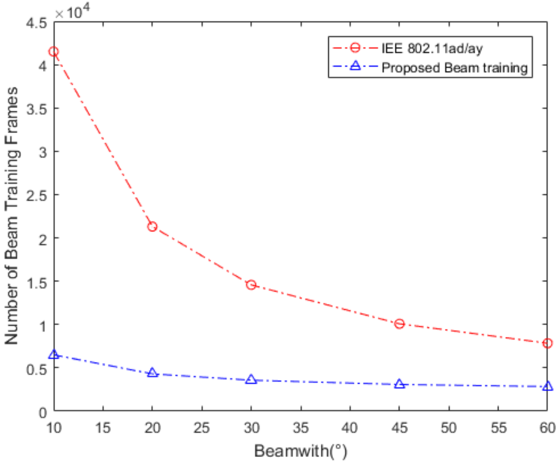


Figure 13: The performance between BFT in IEEE802.11ad/ay and proposed efficient BFT mechanism

Data Generated

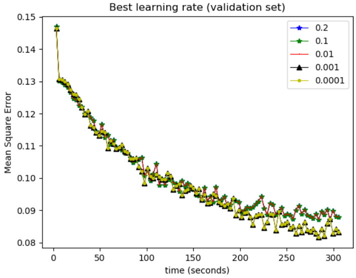
$$SINR_{i,j} = \frac{x_{i,j} P^{r}_{i,j}}{W.N_0} \tag{20}$$

	z0	z1	z2	z3	z4	z5	z6	z7	z8	z9	...	z19990	z19991
0	47.453710	738.315292	1976.976484	37.377212	30.890258	328.140130	219.664054	353.867093	54.916013	76.280024	...	43.684104	76.280024
1	82.035032	95.685662	99.631051	40.346459	452.200670	598.035386	42.526961	85.159898	42.526961	1976.976484	...	54.916013	24.907763
2	68.719952	64.287599	113.050168	46.144706	174.736417	37.377212	248.922117	542.435725	60.270636	738.315292	...	85.159898	32.343720
3	1220.480380	452.200670	738.315292	50.244519	28.262542	38.329459	1661.209407	24.407117	85.159898	142.304673	...	35.576168	118.130447
4	149.508847	68.719952	305.120095	56.618735	28.887110	29.532612	108.290699	157.274263	43.684104	62.230529	...	79.079059	64.287599
5	195.276861	2392.141546	54.916013	66.448376	41.415193	39.318566	26.505723	44.889126	108.290699	79.079059	...	25.956397	738.315292

6 rows × 20000 columns

Figure 14: SNR values Data Frame

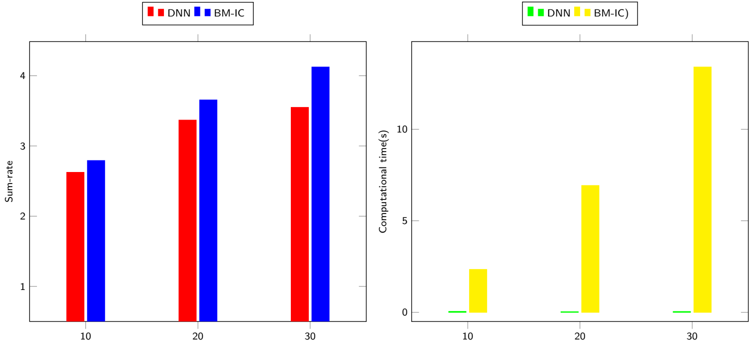
Parameters selection and performance of DNN approach



(a) learning rate selection

Number of STA	Sum-rate		Ratio	Computational time	
	DNN	BM-IC	DNN/BM-IC	DNN	BM-IC
10	2.624	2.792	93.997%	0.048	2.342
20	3.368	3.655	92.136%	0.032	6.926
30	3.549	4.124	86.053%	0.043	13.398

Table 1: Sum-rate and computational time performance of DNN and BM-IC



(a) Sum-rate (b) Computational time(s)

Figure 16: Sum-rate and computational time performance of DNN and BM-IC when the number of STA increase

Conclusion and Perspectives

Conclusion

- Dense mm-Wave with centralized architecture and formulated the mathematical problem which was NP-hard optimization problem
- Increase of sum-rate of both classic and DNN model while the ratio is decrease cause by the augmentation of the interference in the network
- Computational time in DNN approach is more less than when we used the classic BM-IC method

Perspectives

- Conduct a comparative study of our proposed beam selection and other deep learning-based methods as convolutional neural networks and reinforcements learning
- Proceed the same when station are mobile in the network

Thank you for your attention