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Wireless LANs

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| Proposed IEEE 802.11 AIML TIG Technical Report Text for the CSI Compression Use Case |
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| Author(s): |
| Name | Affiliation | Address | Phone | Email |
| Zinan Lin | InterDigital | 111 West 33rd StreetNew York, NY 10120USA |  | Zinan.lin@gmail.com |
| Rui Yang | InterDigital |  |  |
| Xiaofei Wang | InterDigital Inc. | +1-607-592-2727 | Xiaofei.wang@interdigital.com |
| Liangxiao Xin | Zeku |  |  |  |

Abstract

This document contains the proposed technical report text of the IEEE 802.11 AIML TIG, especially for the CSI compression use case.

Revision history:

r0: initial version

r1: updated per comments in AIML meeting on 11/14/2022

r2: updated based on comments in AIML meeting on 11/16/2022

r3: updated 3.1.1 based on the comments from Gaurang and Liangxiao

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	1. Terminologies
	2. Background information
2. **AIML Use cases for IEEE 802.11**

Note: use cases potentially can be organized into different categories

Note: use cases potentially can identify KPIs

* 1. **Use case 1: CSI feedback compression**

In 802.11ax [1] and the draft of 802.11be [2], the AP initiates the sounding sequence by transmitting the NDPA frame followed by a NDP which is used for the generation of V matrix at the beamformee. Upon the receipt of the NDP from the beamformer, the beamformee applies a compression scheme (i.e., Givens rotations) on the V matrix and feeds back the angels in the beamforming report frame.

It is indicated in [3] that higher number of spatial streams has been an inevitable trend in WiFi for more than a decade. The preliminary results [3] [4] [5] show that MIMO with a large number transmitter antennas and a large number of spatial streams (e.g., 16 spatial streams) offer remarkable system performance gains on both SU-MIMO and MU-MIMO cases. Multi AP (MAP) may be one potential feature in the next 802.11 generation, e.g. UHR [6] - [9] . Large number of spatial streams combined with MAP feature may further increase the sounding feedback airtime overhead if coordination between APs (e.g., joint transmission/reception, coordinated beamforming) is applied. Large amount of overhead or prolonged sounding procedures may negatively impact the latency and limit the system performance. Therefore, there is a need to reduce the CSI overhead especially when the number of transmitter antennas goes higher or multiple APs perform joint or coordinated transmission.

Some studies (e.g., [10] [11] [12] [13] ) have shown that AI/ML can efficiently reduce the CSI feedback and improve the system throughput. For example, motivated by the nature that the CSI may fall into different clusters due to the channel similarity of nearby STAs, iFOR algorithm [10] applies the unsupervised learning, K-mean, to the CSI compression to classify the angle vectors which are derived from V matrix. Simulation results show that for an 8x2 SU-MIMO, iFOR uses around 8% of the number of bits required by the existing feedback mechanism (802.11ax) and boosts the system throughput by up to 52%. In [11] , another unsupervised learning, Deep Neural Network Autoencoder (DNN-AE) is applied to CSI angle vectors and further compresses the derived angles (LB-SciFi) by leveraging the compression capability of DNNs. Experimental results show that LB-SciFi reduces the feedback overhead by 73% and increases the network throughput by 69% on average.

This use case proposes to apply AI/ML technique to CSI feedback schemes to reduce the CSI overhead with minimum loss of PER performance.

KPIs considered in this use case are proposed as follows:

1. **Number of feedback bits per subcarrier group**
2. **Achieved PER**
	1. **Both SU-MIMO and MU-MIMO cases need to be considered**
3. **Additional AIML overhead compared with compression saving**
	1. One example is the ratio between the number of additional bits required by AIML process (including data used for model training/inference [14] , the model parameters, the additional signaling) and the number of bits saved by the CSI feedback scheme. In this example, if the data used for model training that is performed by the AP fully relies on the legacy CSI report, then the additional AIML overhead used for model training/inference may be negligible..
4. **Computation complexity/Latency**:
	1. Additional delay or computation is introduced by AIML processing

Evaluation methodology needs to be established.

* 1. Use case 2
	2. Use case N
1. **Requirements and Potential features analysis (high level)**
	1. Requirements
2. Use case 1: CSI feedback compression
3. Backward compatibility with legacy 802.11
	1. Support backward compatibility and coexistence with legacy 802.11 CSI report schemes
4. Performance should follow the guidance below:
	1. **CSI airtime reduction**: achieve airtime reduction of CSI feedback over 802.11be for a given Nr x Nc MIMO, where Nr is the number of rows in the compressed beamforming feedback matrix, Nc is the number of columns in the compressed beamforming feedback matrix.
	2. **Additional AIML overhead**: minimize the additional overhead used for AIML process. Additional AIML overhead may include the data used for AIML model training/inference [14],the model parameters and additional signaling. The data used for AIML model training/inference [14] can reuse the legacy CSI report data.
	3. **Packet Error rate (PER)**: guarantee minimum SNR loss compared with 802.11be to achieve the target PER (e.g., 1% and/or 10%) at a given MCS in all types of channels [15] .
	4. **Computation complexity/Latency**: minimize the additional computation complexity or latency required by AIML process
	5. Potential features analysis
5. **Technical feasibility analysis**
	1. Standards impact
6. Use case of CSI feedback compression

The standard impact may include:

* Additional signaling (e.g., between AP and non-AP STAs) required by AIML process.
	1. Technical feasibility
1. Use case of CSI feedback compression

 The following metrics will be studied:

* + 1. **Backwark compatibility**: The STAs that supports AIML enabled CSI feedback compression shall support the legacy 802.11 CSI report scheme. This compatibility is expected to be supported since AIML capable STAs are expected to support legacy CSI report scheme.
		2. **Data availability and accessibility**: There are some STAs that are able to use the data to perform AIML model training and/or inference[14] . The data used for model training and/or inference shall be accessible for these STAs.
			- AP/edge computing based AIML: Data may be collected from non-AP STAs. The legacy 802.11 CSI reports may be used as training data.
			- Device computing based AIML: Data should be available at all STAs that support AIML process.
		3. **Hardware/software capability**: The STAs that use AIML to generate the AIML enabled CSI feedback compression shall have the hardware and software capability to support AIML algorithm(s).
			- AP/edge computing based AIML [16] : Extra data and model (e.g., model parameters) exchange may be required to support AP/edge computing based AIML. However, computation is not expected to be located at AP or edge computing resources for which higher computation capabilities is expected.
			- Device computing based AIML [16] : STAs that support AIML may be required to have extra computation capability. Extra data and model (e.g., model parameters) exchange between STAs may also be required to support device computing based AIML.
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