The Road Towards an AI-Native Air Interface (AI-AI) for 6G

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What will future communications look like in 2030? Creating the ‘augmented human’

Augment our Intelligence

Augment our experience

Augment our control

- Learn from/with machines
- Automatic security
- In-body monitoring

- Multi-model mixed reality telepresence
- High resolution mapping
- Mixed reality co-design

- Domestic robots
- Remote & self driving
- Drone/robot swarms

6G to enable a new lifestyle at scale
The enabling foundation for that future...

Six key technologies for 6G

- AI/ML Air-Interface
- New Spectrum Technologies
- Network as a sensor
- RAN-Core Convergence & Specialization
- Extreme Connectivity
- Security and Trust
No component of 5G has been designed by ML
What if 6G was built so that ML could optimize parts of the PHY & MAC if needed?
Possible benefits

- Bespoke waveforms, constellations & pilots
- Optimally adapted to hardware limitations
- Reduced standardization effort
- No heuristic parameter settings
- Faster development & deployment time
- Custom signaling and access schemes
AI-Native Air Interface (AI-AI) for 6G

The AI-AI optimally adapts to different environments, hardware, data, and applications.

"Post Shannon": Not about reliably transmitting bits anymore, but rather serving an application with data in an optimal way.
A roadmap to an AI-Native Air Interface for 6G

1. ML replaces/enhances individual processing blocks

2. ML replaces multiple processing blocks

3. ML designs part of the PHY itself
Case study:
From Neural Receivers to Pilotless Transmissions
SISO doubly-selective channel

Pilots

72 Subcarriers

Resource element (RE)

14 OFDM symbols

Y = H \circ X + N

vec(H) \sim CN(0, RF \otimes RT)

Spectral correlation
- \[ [RF]_{i,k} = \sum_{l=1}^{L} S_l e^{j2\pi l D_s \Delta F (i-k)} \]
- Subcarrier spacing \( \Delta F = 30 \text{ kHz} \)
- Delay spread \( D_s = 100 \text{ ns} \)
- TDL-A power delay profile

Temporal correlation
- \[ [RT]_{i,k} = J_0 \left( 2\pi \frac{v}{c} f_c \Delta T (i-k) \right) \]
- Carrier frequency \( f_c = 3.5 \text{ GHz} \)
- Speed \( v = 50 \text{ km/h} \)

Modulation & Coding
- 64 QAM
- 5G code \( n=1024, r=2/3 \)
Baseline receiver

- Least-squares channel estimation at pilot positions
- Equalization using the nearest pilot
- Exact LLR computation assuming a Gaussian post-equalized channel
- Textbook sum-product BP decoder with 40 iterations
Potential performance enhancements
Deficits of the baseline

Imperfect channel estimation & channel aging lead to
- Mismatched LLR computation
- SNR degradation
Neural demapper (symbol-wise)

\[
R_e \{ \hat{X}_{i,j} \}, \quad I_m \{ \hat{X}_{i,j} \}, \quad SNR_{i,j}, \quad Pos. \text{ enc. } i, \quad Pos. \text{ enc. } j
\]

\[
LLR_{i,j}^{(1)}, \quad \cdots, \quad LLR_{i,j}^{(6)}
\]

Learns grid position-dependent statistics for better LLR computation
Neural demapper (grid-wise)

[Image of neural demapper diagram]

Channel Estimation → Equalization → Decoding

[Re{\hat{X}}, Im{\hat{X}}, SNR] → LLR

72 × 14 × 3 → 72 × 14 × 6

Leverages pilots and data to compensate for channel aging and mismatched LLR computation.
Neural network architecture is key to success

Fully convolutional ResNet

Dilated separable convolutions


Each output value has a receptive field spanning the entire resource grid
Neural receiver

Data-aided channel estimation, equalization, and demapping for unprecedented performance
End-to-end learning with Neural receiver

```
\begin{align*}
C &= \frac{1}{64} \sum_{c \in \hat{C}} c \\
&= \sqrt{\frac{1}{64} \sum_{c \in \hat{C}} |c|^2 - \frac{1}{64} \sum_{c \in \hat{C}} \bar{c}^2}
\end{align*}
```

64x2 trainable weights

Zero-mean unit energy constellation

End-to-end learning enables pilotless transmissions without performance loss
Learned constellation for pilotless communication

F. Ait Aoudia, J. Hoydis, “End-to-end Learning for OFDM: From Neural Receivers to Pilotless Communication”, arXiv2009.05261

How could this be standardized?
Important research topics for end-to-end learning

• New waveforms for new spectrum
• Learning for systems with (extreme) hardware constraints
• Joined communications + X
• Signals conveying a few bits of information
• Application-specific end-to-end learning
• Semantic communications
• Decentralized & federated learning
• Transfer & meta learning
The next frontier: Protocol learning
Emerging a RAN protocol

Can we learn a MAC protocol?

Thank you!