I M P E R I A L

Github Resources

Neuromorphic Semantic Communications for Future Wireless Systems

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Background

The Communications Paradigm Shift: From Bit Accuracy to Semantic Fidelity

- Most semantic communication models are based on **ANNs**:
  - Pros: spectral efficiency, robustness and high performance etc [1].
  - **Cons:**
    - Floating-point computations.
    - Energy-intensive.
    - Additional transmission overhead.

The Intelligence Paradigm Shift: From Deep Learning to Neuromorphic Learning

- **Features:**
  - High energy efficiency.
  - Time-coded spike-based computing.
  - Always-on computation.
  - Biological plausibility.

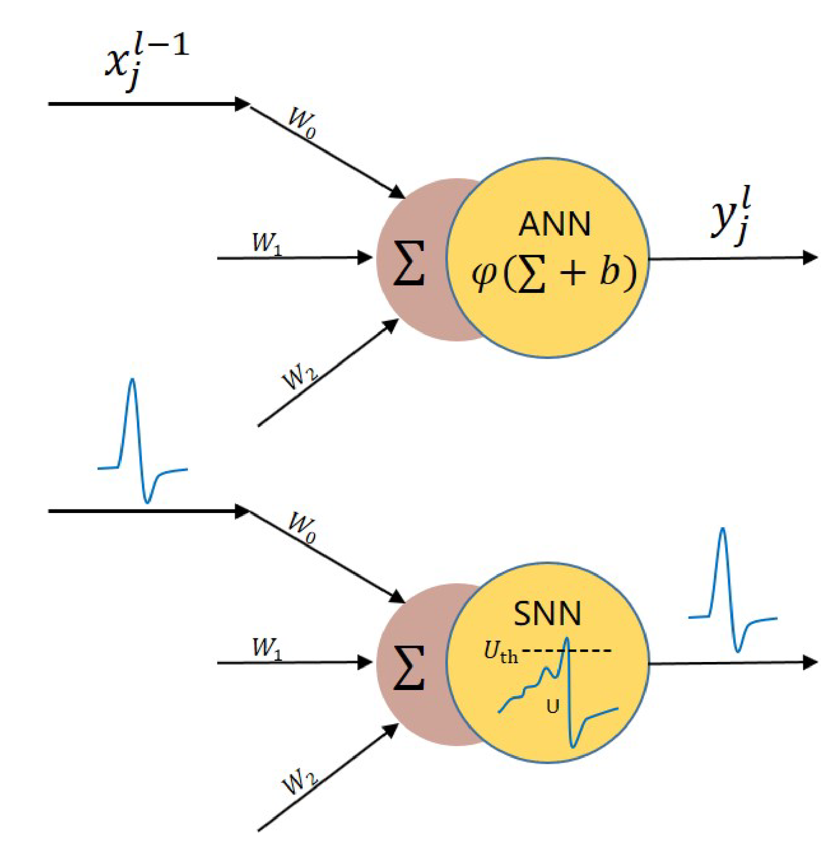


Figure 1: Comparison of ANNs (top) and SNNs (bottom).

SNNs Enabled Neuromorphic Semantic Communications

- **Pros:**
  1. Well-suited for resource-constrained wireless edge scenarios.
  2. Real-time processing with minimal generated data.
  3. Seamless integration of semantic communications into digital channels.
- **However,** most existing works [2]-[4] either focus on idealize channels or over-simplified tasks.

System Model and Contributions

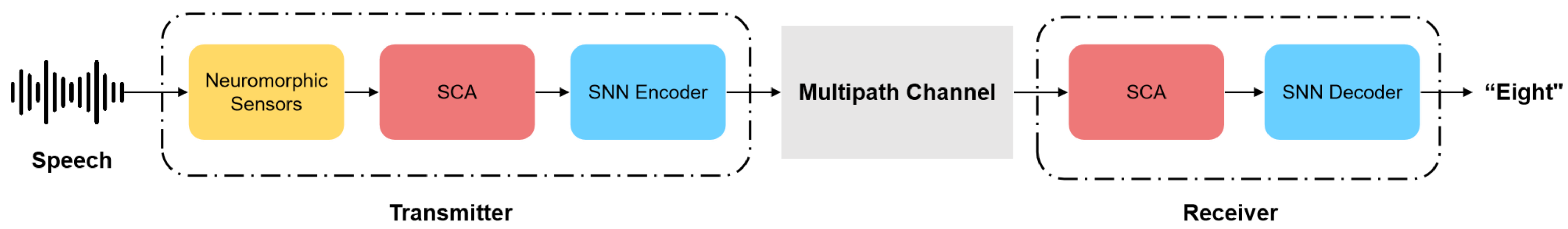


Figure 2: The system model of Att-NeuroSC.

- An **initial** work to build an attention module and optimize spike redundancy for task-oriented neuromorphic semantic communication systems:
  - We developed the **Att-NeuroSC**, a novel task-oriented neuromorphic semantic communication system, to perform remote speech recognition tasks.
  - We introduced an energy-efficient **Spike Cross Attention** module.
  - We proposed a **Spiking Rate Loss** and analysed the spike redunency of SNNs.

Spike Cross Attention

- Energy-efficient attention module tailored for SNNs.
- Jointly learn 'when' and 'where' to focus on important information.
- Improve learning performance and efficiency.

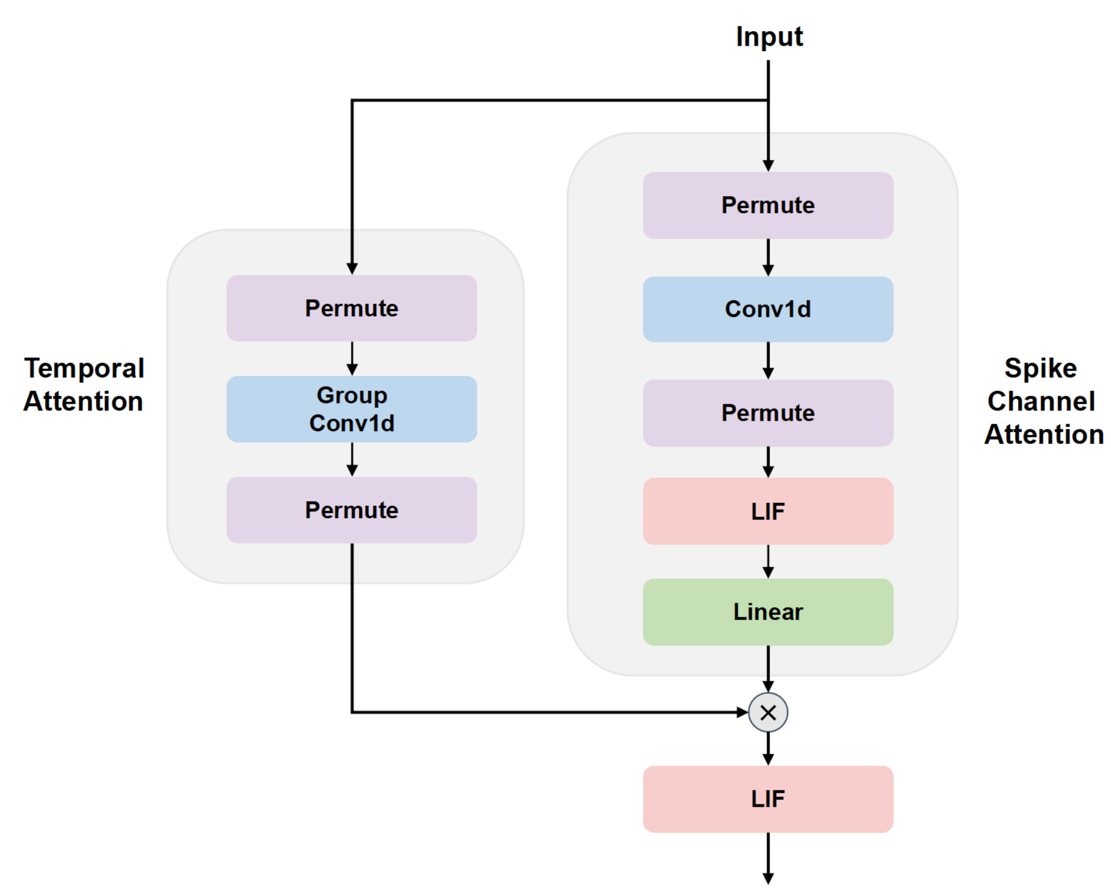


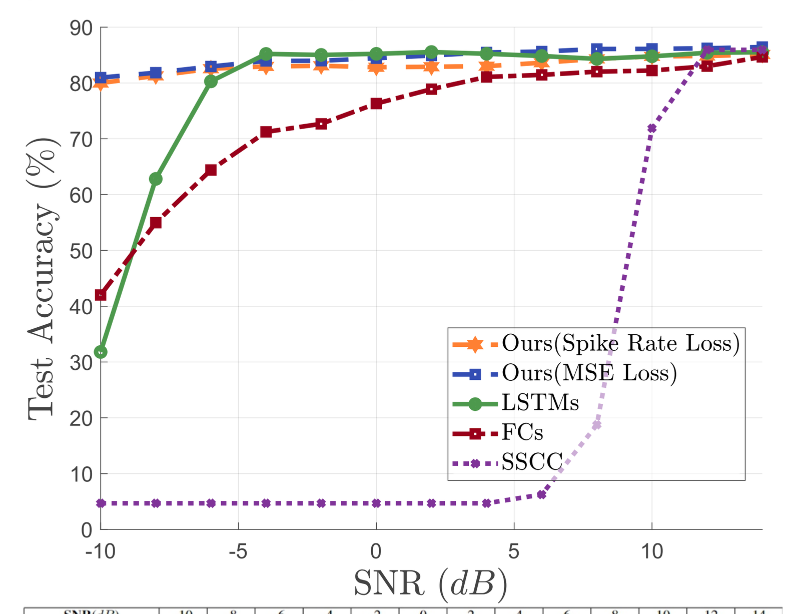
Figure 3: The architecture of SCA module.

Spike Rate Loss

- Reduce spike redundancy of SNNs.
- Introduce a spike penalty into the MSE loss.
- Train with spike rate loss as follows:

$$L = \frac{1}{T}\sum_{t=0}^{T-1}\left[\frac{1}{C}\sum_{i=0}^{C-1}(\hat{y}_{t,i} - y_{t,i})^2\right] + \lambda \cdot \frac{1}{N}\sum_{i=0}^{N-1} o_i^2.$$

Experiments



SNR(dB)	-10	-8	-6	-4	-2	0	2	4	6	8	10	12	14
Spike Reduction(%)	31.63	40.50	44.97	57.31	66.80	67.13	76.06	73.34	84.67	83.65	85.68	88.95	82.88

Figure 4: Test accuracy under different SNR values.

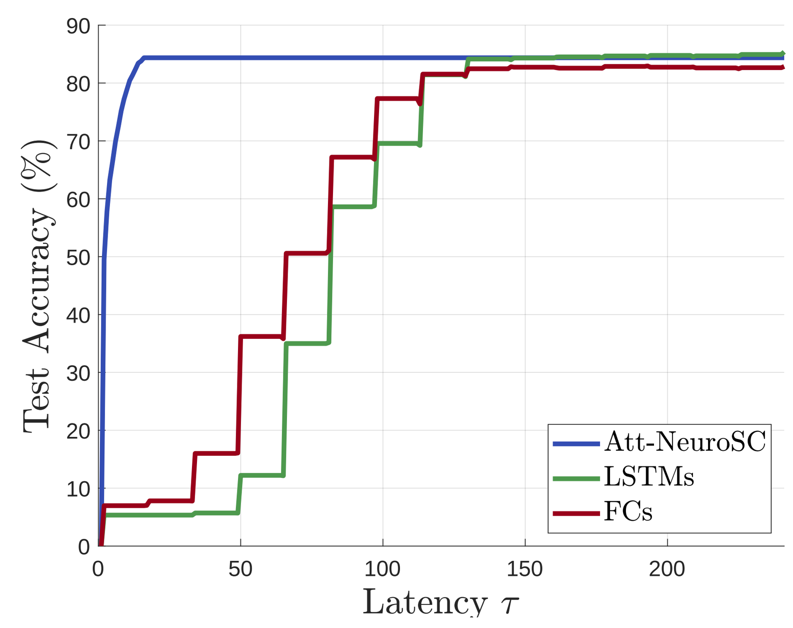


Figure 5: Test accuracy against latency (SNR = 10 dB).

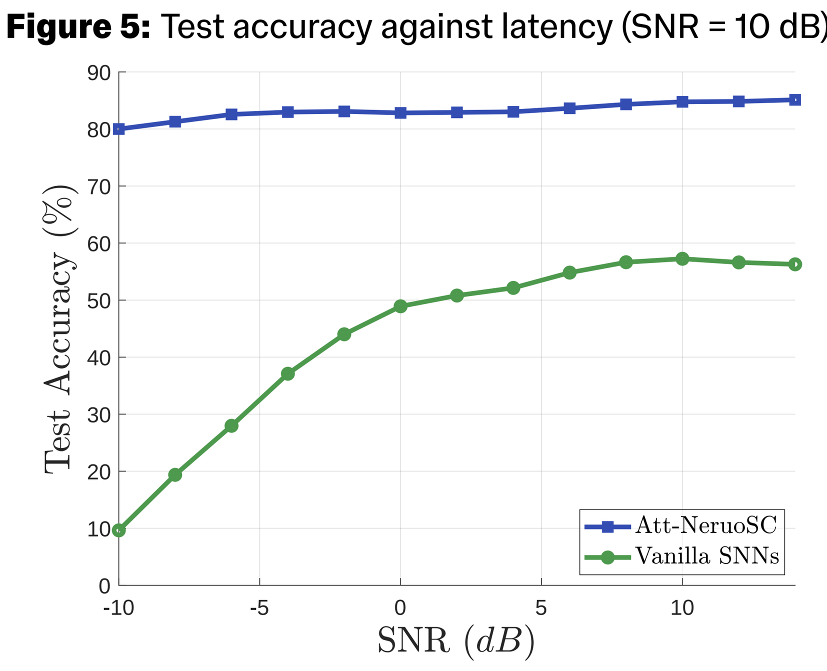


Figure 6: Ablation studies of SCA.

Table 3. Energy Consumption Comparison

Model	Energy Consumption
Att-NeuroSC	3.63 μJ
FCs	11.73 μJ
LSTMs	17.58 μJ

Publication

- **H. Huang** and Y. Liu, "Attention-aware neuromorphic semantic communications," 2024 IEEE 34th International Workshop on Machine Learning for Signal Processing (MLSP), London, UK, 2024, accepted to appear.

Future Work

- Investigating **distributed sensing** and **fast-changing** communication scenarios.
- **Meta-learning** algorithm for fast adaptation to new environments with few-shot pilots.

Reference

1. W. Tong and G. Y. Li, "Nine challenges in artificial intelligence and wireless communications for 6G," IEEE Wireless Commun., vol. 29, no. 4, pp. 140–145, 2022.
2. N. Skatchkovsky, H. Jang, and O. Simeone, "End-to-end learning of neuromorphic wireless systems for low-power edge artificial intelligence," in Proc. Asilomar Conf. Signals, Syst., and Comput., 2020, pp. 166–173.
3. J. Chen, N. Skatchkovsky, and O. Simeone, "Neuromorphic wireless cognition: Event-driven semantic communications for remote inference," IEEE Trans. Cogn. Commun. Netw., vol. 9, no. 2, pp. 252–265, 2023.
4. M. Wang, J. Li, M. Ma, X. Fan, and Y. Tian, "SNN-SC: A spiking semantic communication framework for feature transmission," arXiv preprint arXiv:2210.06836, 2022.