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Advancing Image Transfer Through Semantic-aided Approaches: A Multi-modal Exploration

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Session 7 – Enabling technologies

Outline

- **Semantic Communication**
- **Motivation for Advancing Semantic Communication**
- **Challenges in Current Image Transfer Systems**
- **Proposed Solution: Multi-modal Image Transfer**
- **System Overview**
- **Multimodality in Semantic Communication**
- **Comparison of Secondary Mode**
- **Results**
- **Conclusion**

Semantic Communication

Semantic Communication focuses on the **meaning** of the data rather than transmitting raw data

Traditional Communication: Focuses on bit-level accuracy and raw data transfer

Objective: Reduce data transmission size and improve efficiency

"HOW PRECISELY DO THE TRANSMITTED SYMBOLS CONVEY THE DESIRED MEANING?"

THE SEMANTIC PROBLEM

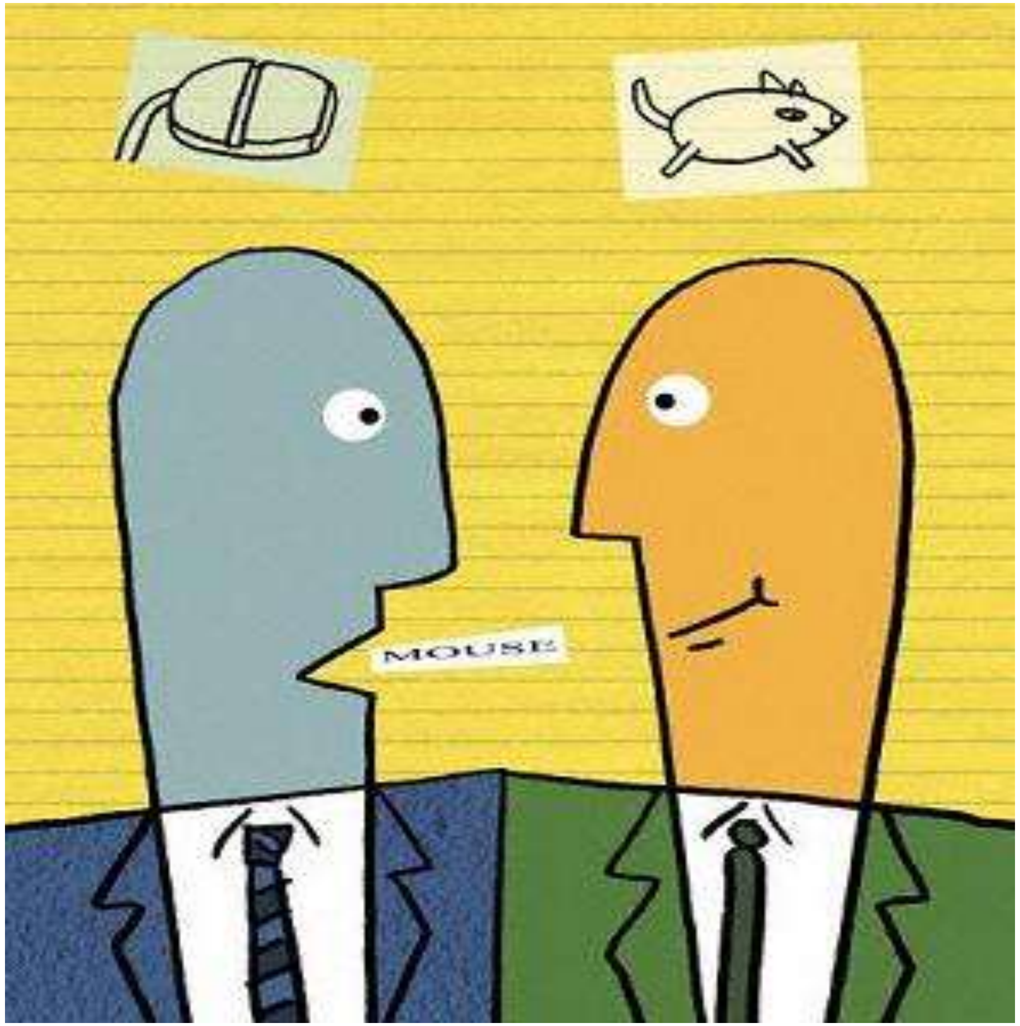


Image Source: Fixing the Economists. (2013, November 5). Is Real Communication Possible? Berkeley's Particularism and Lacan's Semantic Slippage.

Motivation for Advancing Semantic Communication

5G to 6G Transition: Emerging technologies (AI, IoT, autonomous systems) require **higher data rates** and more efficient communication

Challenges in 5G: Latency, **bandwidth constraints**, and lack of real-time adaptability

Solution: SC prioritizes meaning to enhance efficiency, lower latency, and reduce bandwidth consumption

Challenges in Current Image Transfer Systems

Conventional methods transfer raw pixel data, leading to large bandwidth consumption

Single-modality image transmission (e.g., text) fails to capture the full context of images

Need for Innovation: Can we reduce data while maintaining the semantic richness of the image?

Proposed solution: multi-modal image transfer

Introduced a multi-modal approach: Primary Mode: Text captions generated using deep learning models (BLIP)

Secondary Mode: Line art or other structural representations to enhance image fidelity

This approach **balances** data reduction and the preservation of semantic details

→ There is a man holding a lit candle in the desert

→ There is a lizard that is lying down on the ground

Advantages of Image Captioning

- Data Reduction
- Semantic Fidelity

System Architecture Overview

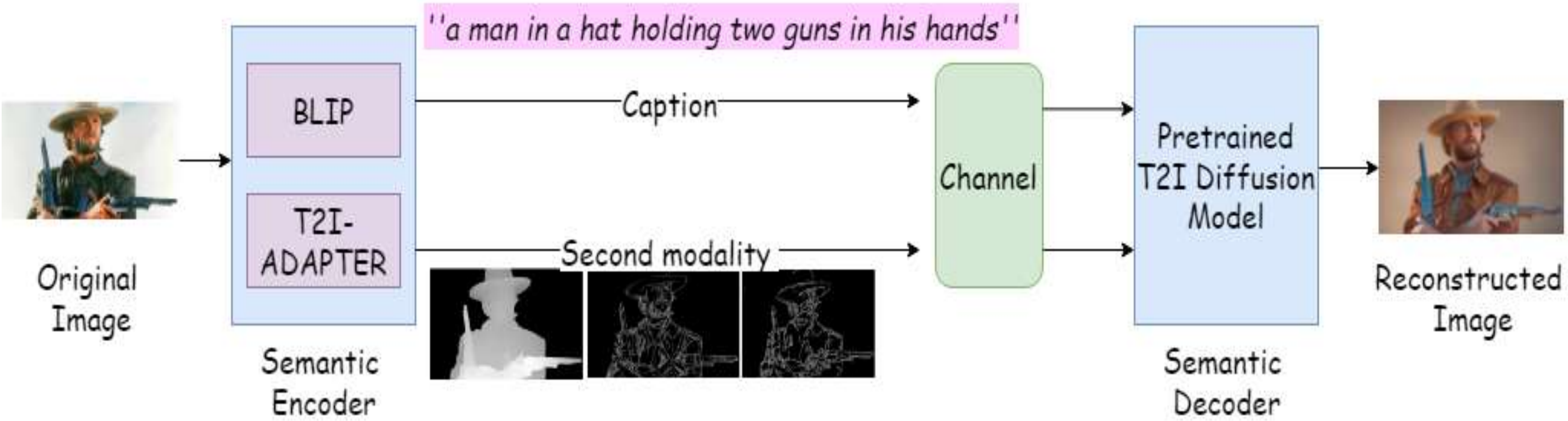


Fig.1 Semantic-aided image transfer through multi-modality

Multi-Modality in Semantic Communication

Why Multi-Modality?

- Single modality (captions only) misses important visual and spatial details
- Multi-modality (captions + structural data) provides a **richer** and **more complete** representation of the image
- Key Benefits:

Increased fidelity with lower data transmission requirements

Better semantic interpretation of images at the receiving end

Comparison of Secondary Modes

- **Depth Map**: Provides spatial information by assigning depth values to pixels
- **Canny Edge**: Focuses on edge detection by locating changes in intensity (used for structural outline)
- **Line Art**: Emphasizes structure and form without color or shading (selected for best balance between fidelity and data reduction)

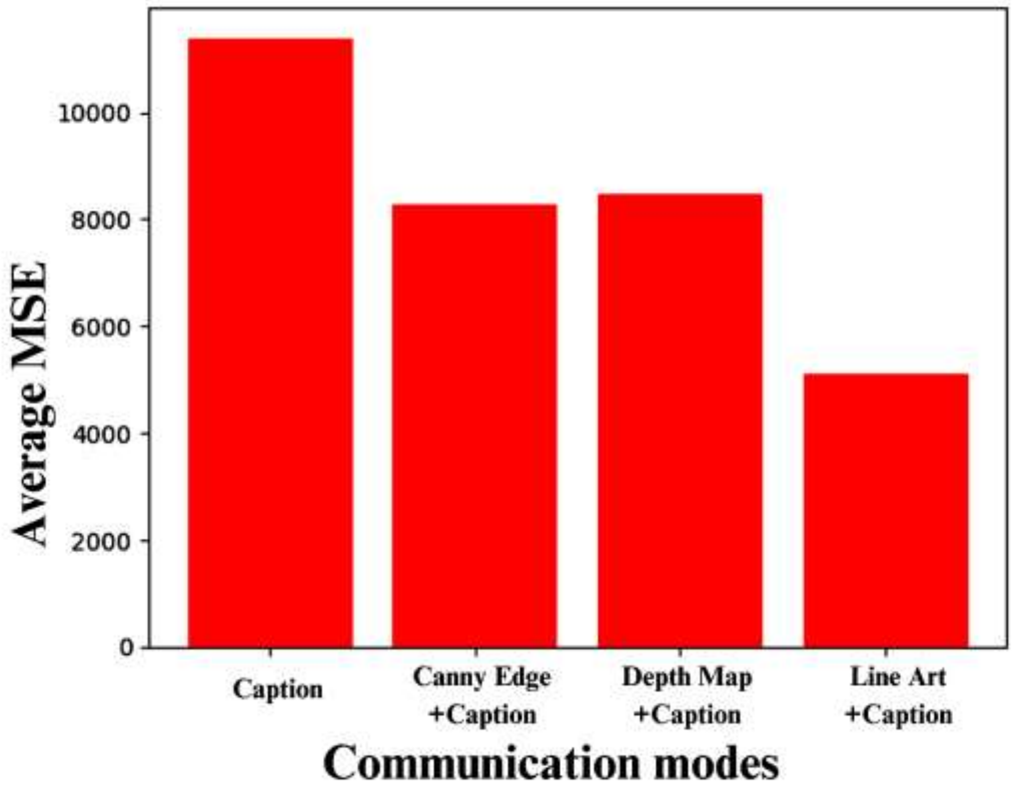
Performance Metrics for Evaluation

- **Mean Squared Error (MSE):** Measures the pixel-level error between the original and reconstructed images
- **Peak Signal-to-Noise Ratio (PSNR):** Indicates the signal quality; higher values represent better reconstructions
- **Structural Similarity Index (SSI):** Evaluates perceptual similarity, focusing on how closely the reconstructed image matches the original from a human visual perspective

Overall Comparison

MODE	ORIGINAL IMAGE	SEMANTIC ENCODING	SEMANTIC DECODING	MSE	SSI	PSNR
LINEART				*7414.3*	*0.6447*	*9.430*
CANNYE--DGE				*1462.4*	*0.4652*	*6.4788*
DEPTHMAP				*15216.3*	*0.4451*	*6.3077*

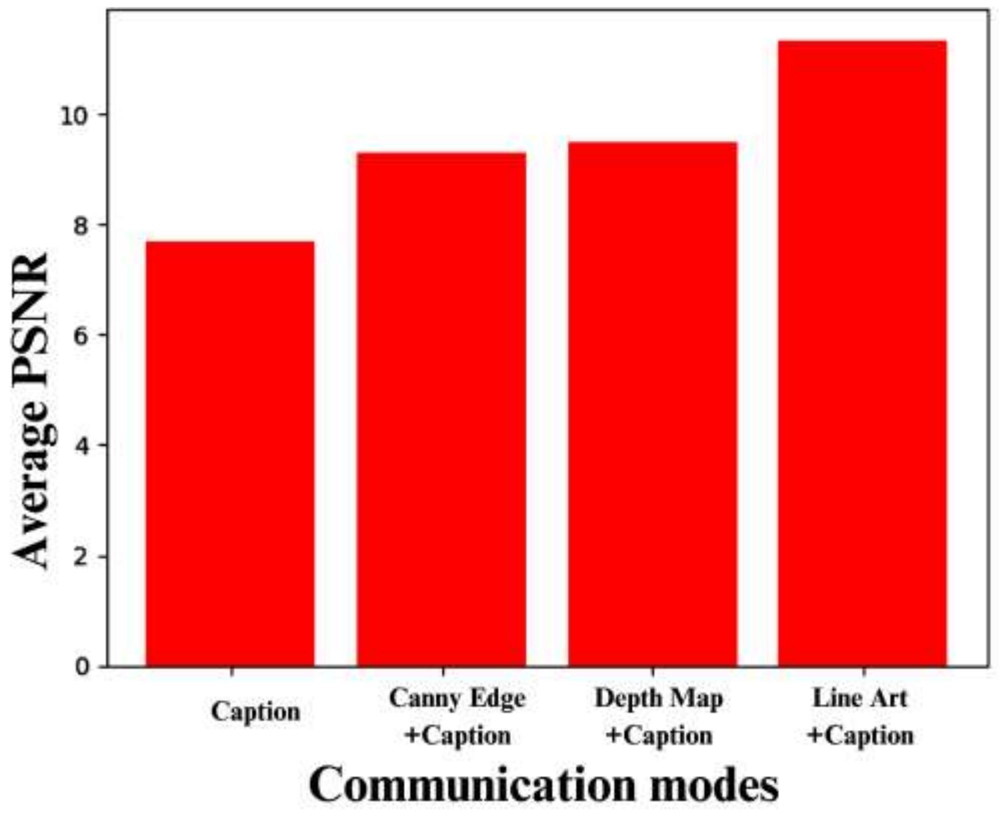
Results: MSE Performance



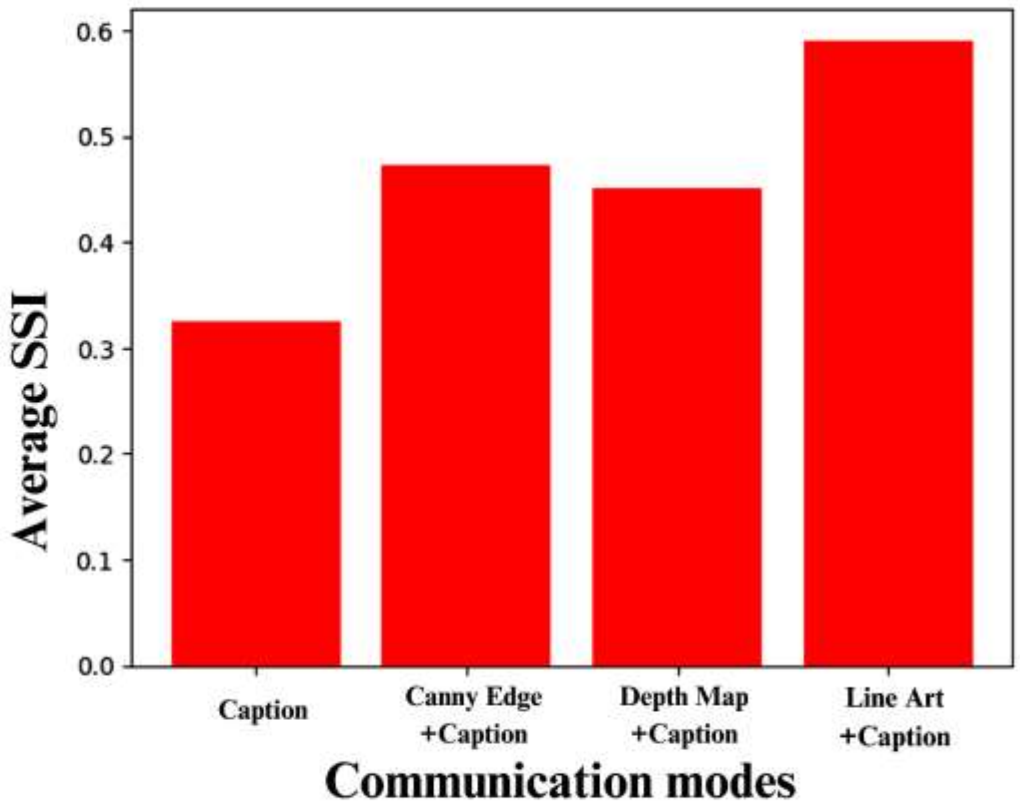
- **Observation**: Lower MSE indicates better image reconstruction accuracy
- **Finding**: Line art consistently shows the lowest MSE, outperforming other modes such as Canny Edge and Depth Map
- **Conclusion**: Line art is the most effective secondary mode for minimizing reconstruction errors

Results: PSNR Performance

- **Observation**: Higher PSNR values reflect better preservation of signal quality
- **Finding**: Line art delivers the highest PSNR among the tested modes, indicating that it maintains the highest fidelity in image reconstruction



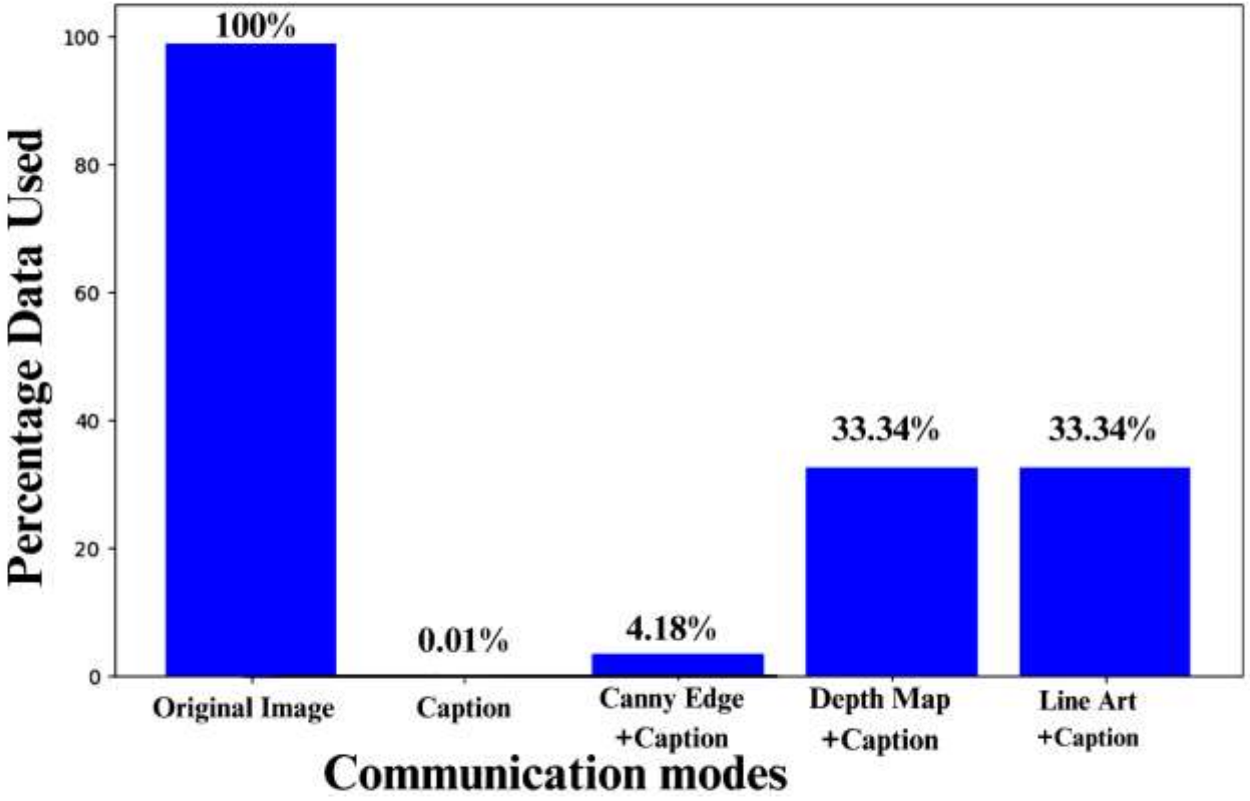
Results: SSI Performance



- **Observation**: SSI measures the visual similarity of reconstructed images to the original
- **Finding**: Line art shows the highest SSI, making it the most effective at producing images that are perceptually similar to the original

Data Reduction Analysis

- **Original Image**: 728x492 pixels, requiring 8.59 million bits
- **Caption + Line Art** Significant data reduction, with line art requiring 2.86 million bits and the caption requiring 312 bits
- **Conclusion**: This multi-modal approach reduces the data required by nearly **65%** while maintaining image fidelity



Conclusion

- **Summary**:
    - Proposed a novel **multi-modal system** for semantic-aided image transfer using **captions and line art**
    - Demonstrated significant **data reduction** with minimal loss in image quality
    - **Line art** emerges as the optimal second mode for preserving image structure and minimizing data
- **Future Work**:
    - Investigate the addition of **color consistency** to further improve reconstruction accuracy
    - Explore more complex images and **dynamic content** in real-time applications

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Thank you for your attention.
Any questions?

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Thank you!