International Journal of Information Science and Applications.
ISSN 0974-2255 Volume 18, Number 1 (2026), pp. 1-6

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Semantic Communication for 6G Wireless Networks: A Review of Deep Joint Source-Channel Coding, Architectures, and Open Challenges

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Abstract:
Semantic communication proposes a departure from the classical Shannon paradigm, in which a communication system is designed solely to reproduce transmitted bits at the receiver with minimal error, toward systems that instead aim to convey the meaning or task-relevant content of a message, potentially tolerating bit-level errors that do not affect the semantic outcome. Enabled by advances in deep learning, particularly deep joint source-channel coding, semantic communication has emerged as one of the technologies most closely associated with the vision of a native artificial-intelligence sixth-generation (6G) network. This paper reviews the conceptual foundations that distinguish semantic communication from classical bit-level communication, surveys deep joint source-channel coding architectures for text, image, and video transmission, and discusses the roles of large language models and multimodal foundation models in recent semantic communication system designs. Security and privacy considerations specific to semantic communication, including adversarial robustness of learned encoders and decoders, are also reviewed. The paper concludes with a discussion of open challenges, including the absence of a general semantic-level performance metric, interoperability across heterogeneous semantic encoders, and the standardization effort required to move semantic communication from research prototypes toward native inclusion in future 6G specifications.

Keywords: semantic communication, 6G, deep joint source-channel coding, goal-oriented communication, large language models, task-oriented transmission

1. Introduction

Classical wireless communication system design has, since Shannon's foundational information theory, treated the goal of a communication link as the faithful reproduction of transmitted bits at the receiver, independent of what those bits represent or how they will ultimately be used. This bit-level fidelity criterion has served as a robust and general design principle across successive cellular generations, but it also implies that a communication system expends resources reproducing information exactly, even when only a small fraction of that information is relevant to the task the receiver ultimately performs, such as classifying an image, answering a question, or executing a control action.

Semantic communication reframes this objective: rather than minimizing bit error rate, a semantic communication system aims to preserve the meaning, or task-relevant content, of a transmitted message, which may permit substantial compression relative to bit-exact transmission when the receiver's ultimate goal tolerates some loss of literal fidelity. This idea, foreshadowed in early information-theoretic discussions of communication levels beyond the technical (bit-accurate) level, has become newly practical with the maturation of deep learning, particularly through deep joint source-channel coding architectures that learn end-to-end mappings from source content directly to channel symbols, bypassing the separate source-coding and channel-coding stages of classical system design. This review is organized as follows. Section 2 reviews related survey literature. Section 3 discusses the conceptual foundations of semantic communication. Section 4 surveys deep joint source-channel coding architectures across modalities. Section 5 discusses the emerging role of large language and multimodal foundation models. Section 6 reviews security and privacy considerations. Section 7 discusses open challenges, and Section 8 concludes the paper.

2. Related Work

A growing body of survey literature has documented the rapid development of semantic communication research. Early work established deep learning-enabled semantic communication systems for text transmission, demonstrating that jointly learned source-channel encoders could outperform separate source- and channel-coding pipelines under certain channel conditions, particularly at low signal-to-noise ratios where classical separate coding schemes suffer a sharp performance cliff. This was extended to image and video transmission through deep joint source-channel coding architectures incorporating attention mechanisms and task-oriented objectives, and to broader system-level surveys covering semantic edge computing, architecture design, and the roadmap toward native inclusion of semantic communication in 6G standardization efforts. Other recent surveys have focused specifically on the security and privacy implications of learned semantic encoders and decoders, noting that the adversarial robustness properties of semantic communication systems differ meaningfully from those of classical, non-learned communication systems. This paper synthesizes these strands into a structured overview aimed at readers new to the area as well as researchers seeking a current reference point.

3. Conceptual Foundations

3.1 Levels of Communication

Semantic communication research commonly distinguishes between three conceptual levels of communication problems: the technical level, concerned with accurately transmitting symbols; the semantic level, concerned with conveying the intended meaning of those symbols; and the effectiveness, or pragmatic, level, concerned with whether the conveyed meaning produces the desired effect or action at the receiver. Classical communication system design addresses only the technical level, treating meaning and effect as outside its scope. Semantic communication explicitly targets the semantic level, and goal-oriented or task-oriented communication, a closely related concept, targets the effectiveness level directly, optimizing the transmitted signal for the success of a downstream task, such as a classification or control decision, rather than for reconstruction fidelity at any intermediate level.

3.2 Deep Joint Source-Channel Coding

The predominant technical mechanism used to realize semantic communication is deep joint source-channel coding (DJSCC), in which an encoder neural network maps source content, such as an image or a piece of text, directly to a sequence of channel symbols, and a corresponding decoder neural network maps received, noise-corrupted symbols back to a reconstruction or task output, with the entire pipeline trained end to end against a task-relevant loss function rather than a strict bit-fidelity criterion. Because the channel is typically modeled as a differentiable layer during training, for example as an additive noise layer, DJSCC architectures can adapt their learned representations to the specific noise and fading characteristics of the channel used during training, a property that gives them the graceful degradation behavior at low signal-to-noise ratios frequently reported in the literature, in contrast to the sharp performance cliffs exhibited by separate source- and channel-coding schemes once the channel deviates from the code's design point.

4. Architectures Across Modalities

4.1 Text Semantic Communication

Text-oriented semantic communication systems typically combine a neural language encoder, often built on transformer or recurrent architectures, with a learned channel encoder, optimizing jointly for a semantic similarity metric, such as sentence-level embedding distance, rather than exact word-level reconstruction. Iterative and attention-based designs have been proposed to further improve robustness to channel noise while preserving semantic content under aggressive compression.

4.2 Image and Video Semantic Communication

Image semantic communication research has explored deep learning-based semantic coding schemes that compress images by preserving features relevant to a downstream task, such as scene classification, rather than pixel-level fidelity, with reported studies including task-oriented image transmission for unmanned aerial systems and wireless image retrieval at the network edge. Video semantic communication extends these ideas temporally, with deep-learning-aided video transmission systems designed to prioritize semantically or perceptually important content within a video stream under constrained channel capacity.

4.3 Multi-Task and Multimodal Systems

More recent work moves beyond single-modality, single-task semantic communication toward unified systems capable of supporting multiple tasks or multiple data modalities within a shared semantic encoding framework, motivated by the observation that a network serving diverse 6G applications, from video streaming to sensor telemetry, will need to support heterogeneous semantic objectives without deploying a separate, narrowly trained encoder for each one.

5. Large Language and Foundation Models in Semantic Communication

The rapid development of large language models (LLMs) and multimodal foundation models has begun to influence semantic communication system design, with recent work proposing LLM-driven semantic communication systems for visual transmission and large AI model-empowered multimodal semantic communication frameworks that exploit the broad, pre-trained representational capacity of foundation models rather than training narrow, task-specific semantic encoders from scratch. This direction is closely tied to the broader vision of AI-native 6G networks, in which large pre-trained models are argued to serve as reusable, general-purpose building blocks across multiple network functions, including semantic communication, rather than requiring bespoke models for each individual task.

6. Security and Privacy Considerations

Because semantic communication systems rely on learned neural encoders and decoders rather than fixed, analytically specified codes, they inherit security and robustness considerations familiar from the broader deep learning literature, including vulnerability to adversarial perturbations that are imperceptible to the intended semantic task but can cause a learned decoder to fail or misclassify. Recent surveys examine physical-layer adversarial robustness specific to deep learning-based semantic communication systems, as well as approaches to secret key generation and privacy protection tailored to semantic communication, for example in reconfigurable intelligent surface-assisted deployments where the surface's channel-shaping capability has been proposed as an additional resource for secure key generation.

7. Open Challenges

Several challenges remain before semantic communication can move from research prototypes toward broad deployment. A general, agreed semantic-level performance metric analogous to bit error rate for classical systems remains an open problem, since semantic similarity is task- and modality-dependent, complicating fair comparison across proposed systems. Interoperability is a related concern: because semantic encoders and decoders are typically trained jointly and in a task-specific manner, ensuring that encoders and decoders from different vendors or research groups can interoperate, analogous to standardized bit-level modulation and coding schemes today, is a substantially harder problem than in classical communication system design. Robustness and reliability under distribution shift, where deployment data differs from training data, and computational cost on resource-constrained user devices, also remain practical barriers. Finally, standardization bodies have only recently begun to explore how semantic communication might be incorporated into 6G specifications, and the roadmap for doing so, including how semantic-level objectives would coexist with existing bit-level quality-of-service guarantees, remains an active area of discussion.

8. Conclusion

Semantic communication represents a conceptual shift in wireless system design, from optimizing for bit-level fidelity toward optimizing for the preservation of meaning or task-relevant content, made increasingly practical by advances in deep joint source-channel coding and, more recently, large pre-trained foundation models. This review has summarized the conceptual foundations distinguishing semantic from classical communication, surveyed architectures across text, image, video, and multimodal domains, and discussed the security considerations and open challenges that continue to shape this research area. As 6G standardization discussions progress, resolving questions around semantic-level performance metrics, interoperability, and robustness will be central to determining whether semantic communication moves from an active research topic into a deployed network capability.

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