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# A Study on Deep JSCC for Robust Wireless Image Transmission in 6G Networks

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## Abstract

The surge of visual data, particularly images and videos, makes robust wireless visual communication indispensable in the digital age. With the advent of sixth-generation (6G) networks featuring ultra-high data rates and applications like XR and telemedicine the demand for efficient image transmission is clear. Traditional communication systems, relying on independent source and channel coding, fail to perform adequately in dynamic wireless environments.

Deep Joint Source Channel Coding (Deep JSCC) emerges as a transformative approach that integrates data compression and error protection at the source-channel level, utilizing advancements in deep learning. Advanced architectures, such as autoencoders and adaptive schemes, provide enhanced perceptual quality and adaptability across varying channel conditions.

This review highlights significant progress in Deep JSCC for wireless image transmission in 6G networks, focusing on theoretical foundations and applications in IoT, immersive XR, telemedicine, and vehicular communications. It also addresses challenges like computational complexity and standardization, while identifying future opportunities in semantic communications and green AI.

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Keywords: (Deep JSCC), 6G Wireless Networks, Robust Image transmission, Semantic Communications, (IoT), (XR), Machine Learning for Communications.

# دراسة حول الترميز المشترك العميق للمصدر والقناة لنقل الصور اللاسلكي الموثوق في شبكات الجيل السادس

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**الملخص:**

يشهد العالم تدفّقًا هائلًا للبيانات البصرية، خاصة الصور ومقاطع الفيديو، مما يجعل الاتصال البصري اللاسلكي المتين ضرورة لا غنى عنها في العصر الرقمي. ومع ظهور شبكات الجيل السادس (6G) التي تتميز بمعدلات بيانات فائقة الارتفاع وتطبيقات مثل الواقع الممتد (XR) والرعاية الصحية عن بُعد أصبح الطلب على نقل الصور بكفاءة أمرًا واضحًا.

تعتمد الأنظمة التقليدية للاتصالات على الترميز المنفصل للمصدر والقناة، لكنها تُظهر أداءً ضعيفًا في البيئات اللاسلكية المتغيرة. وهنا يبرز الترميز العميق الموحّد للمصدر والقناة (Deep JSCC) كمنهجية ثورية تدمج بين ضغط البيانات والحماية من الأخطاء في مستوى واحد، مستفيدة من التقدّم في تقنيات التعلم العميق. وتوفر البُنى المتقدمة، مثل الشبكات التلقائية (Autoencoders) والمخططات التكيفية، جودة إدراكية محسّنة وقدرة أعلى على التكيّف مع ظروف القناة المختلفة.

يستعرض هذا البحث أبرز التطورات في تقنية Deep JSCC لنقل الصور لاسلكيًا ضمن شبكات الجيل السادس، مع التركيز على الأسس النظرية والتطبيقات في إنترنت الأشياء، وتجارب الواقع الممتد، والطب عن بُعد، والاتصالات في المركبات. كما يناقش التحديات مثل التعقيد الحسابي وقضايا توحيد المعايير، ويحدد فرصًا مستقبلية واعدة في الاتصالات الدلالية والذكاء الاصطناعي.

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**الكلمات المفتاحية:** (Deep JSCC)، شبكات الجيل السادس اللاسلكية، نقل الصور القوي، الاتصالات الدلالية، (IoT)، (XR)، التعلم الآلي للاتصالات.

## I. Introduction

As the digital age progresses, visual data, particularly images and videos, has become the primary means of communication across various applications, including social networking, telemedicine, autonomous driving, immersive extended reality (XR), and the Internet of Things (IoT). The upcoming sixth-generation (6G) wireless networks will provide the ultra-reliable, high-throughput, and low-latency communication services essential for these applications. Consequently, efficient wireless transmission of visual data is crucial for the future communications ecosystem [1],[2].
However, the reliable delivery of visual data faces challenges, as wireless channels are fragile and susceptible to noise, fading, and interference, which can lead to quality degradation or data loss. Traditionally, image and video transmission has followed the Shannon separation principle, which treats source coding (compression) and channel coding (error correction) independently. While straightforward, this separation can result in suboptimal performance, particularly under dynamic conditions [3],[4].
Joint Source Channel Coding (JSCC) was developed to bridge this gap by combining compression and error correction into a unified framework, allowing for end-to-end optimization [5], [6]. Recent advancements in deep learning have further extended this concept into Deep JSCC techniques, which use neural networks to convert image pixels into channel symbols. With the rise of 6G networks and the demand for ultra-reliable low-latency communication (URLLC) and data-intensive services, Deep JSCC presents a promising solution [7], [8].

This review article examines Deep JSCC techniques, their architectures, evaluation metrics, and applications in wireless image transmission, while addressing their potential in meeting 6G requirements and highlighting areas that need further research. Illustrations and the comparative Table 2 will clarify the distinctions between conventional approaches and Deep JSCC, as well as summaries the latest methods in the field.

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## II. The Imperative for Robust Visual Communication in 6G Networks and JSCC Foundations

The increased dependence on visual data, such as photos and videos, inspired the progression of recent communication systems. New applications such as telemedicine, autonomous driving, extended reality (XR), and holographic communication require the wireless transmission of high-quality visual content with tight constraints on the throughput, latency, and reliability. These requirements are expected to be further enhanced with the deployment of sixth-generation (6G) networks, aimed at accommodating data rates on the order of terabits per second, latency lower than a millisecond and providing ubiquitous global coverage [1], [2],[8]. In this chain of thoughts, clear visual communication is relevant as a major bottleneck. Wireless channels are by essence lossy and degrade the transmitted visual data due to fading, interference and additive noise. The perception of users is affected, in a non-controlled loop fashion, by every small error during the data transmission process, and this is particularly evident in compressed images and videos; as a matter of fact, some transmission errors are immediately perceivable to even non-expert users. This vulnerability highlights the requirement for transmission schemes that are immune to both channel degradations and efficiency. In the course of history, communication systems have pursued a separation principle introduced by Shannon, where design source coding (such as JPEG, HEVC, BPG and so on) is isolated from channel coding (such as Turbo or LDPC). Conceptually optimal under infinite block length, this detachment will, however, become suboptimal in practice, notably so while accounting for the challenges of dynamic wireless settings and latency-sensitive visual services [3]. The limitations are twofold:

source coding causes compression artifacts to magnify the effect of transmission errors, while the extra redundancy due to channel codes is not enough to deal with unpredictable channel impairments.

Hence, there is a large performance gap between this theory and the practical implementation for wireless visual information transmission due to the space source channel coding separation. A promising candidate which bridges this gap is JSCC. In contrast to the conventional approaches that separate compression and error protection, JSCC allows both of these systems to be optimized from

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end-to-end for the best possible communication performance. By potentially combining the statistics on the source with those of the channel, JSCC becomes more robust, especially under time-varying wireless conditions [5],[6]. The development of Deep JSCC, which employs neural networks to learn mappings from images to channel symbols directly, is another breakthrough that has advanced this paradigm. These models do not rely on handcrafted code designs, but rather data-driven learning to be flexible and robust, which are critically important for 6G networks with ultra-high data rates[3].

## III. Deep JSCC Architectures and Approaches

Recent advancements in deep learning have established Deep Joint Source-Channel Coding (Deep JSCC) as a practical and robust framework for future wireless visual communication. Deep JSCC architectures can typically be categorized into three main groups:

a) End-to-end autoencoder architectures.
b) Adversarial and perceptual-loss approaches.
c) Hybrid and adaptive Deep JSCC models[3][7].

The Deep JSCC framework, illustrated in Figure 1, uses an autoencoder design in which a convolutional neural network (CNN) encoder compresses the input image into a latent representation for wireless transmission. Subsequently, a CNN decoder reconstructs the received signal back into an image.
To demonstrate the influence of different training objectives on reconstruction quality, Figure 2 presents a visual comparison among the original image, the mean squared error (MSE)-based reconstruction, and the perceptual-loss reconstruction. The results indicate that while MSE optimization yields higher peak signal-to-noise ratios (PSNR), it often results in lower perceptual quality. In contrast, perceptual-loss methods produce more visually realistic outputs despite lower PSNR values.

Building on these observations, Table 1 provides a comparative summary of the main Deep JSCC approaches: autoencoder-based, GAN-based, and hybrid/adaptive models. This table highlights their strengths, limitations, and suitable application scenarios within 6G wireless systems.

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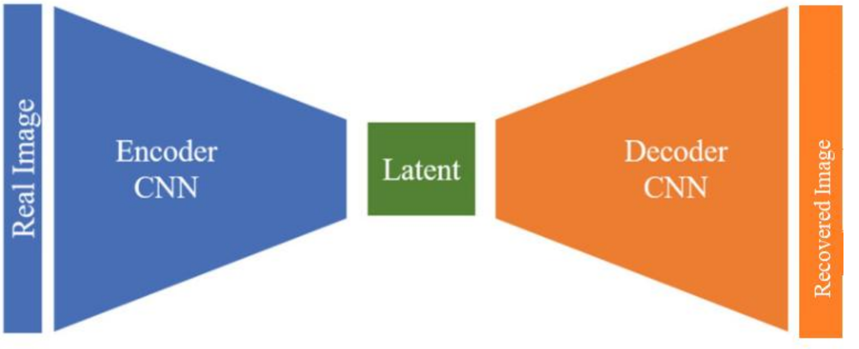
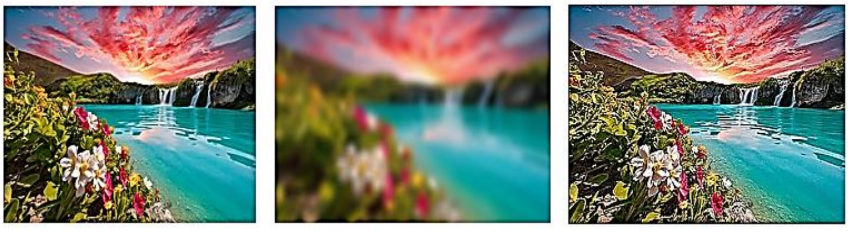



Figure 1. Autoencoder-based Deep JSCC architecture [9]



Original (Reference) | MSE Reconstruction – High PSNR, Low Perceptual Quality | Perceptual Loss Reconstruction – Lower PSNR, Higher Perceptual Quality

Figure 2. Visual comparison of Deep JSCC image reconstruction: original image, MSE-based reconstruction, and perceptual-loss (GAN-based) reconstruction.
Illustration designed by the author

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## Comparative Insights and Trade-offs

**Table 1. Comparative analysis of Deep JSCC approaches: strengths, limitations, and suitable applications in 6G, [3] [5],[6],[10].**

| Approach | Strengths | Limitations | Suitable Applications in 6G |
|---|---|---|---|
| Autoencoder based | End-to-end optimization, simple design, efficient | Limited perceptual quality | IoT sensing, real-time time low complexity tasks |
| GAN-based | High perceptual quality, visually realistic output | High training cost, instability, High training cost, instability, computationally | Telemedicine, holography, immersive XR |

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| | | intensive (GPU heavy) | |
| Hybrid/Adaptive | Flexible, robust under varying channels | High complexity in adaptive control mechanisms | Vehicular comms, XR streaming, mission-critical apps |

Autoencoder-based approaches offer simple end-to-end optimization and reliable performance for low-complexity 6G applications. In contrast, GAN-based models, while computationally intensive and costly to train, excel in producing highly realistic image reconstructions. Hybrid and adaptive methods provide greater flexibility and robustness in dynamic, mission-critical 6G environments. The choice among these methods depends on trade-offs between visual quality, computational demands, system complexity, and reliability requirements.

## IV. Applications in 6G Scenarios

(Deep JSCC) has strong potential to enhance visual communication reliability and efficiency across various 6G application domains. this part highlights four key scenarios where Deep JSCC is expected to play a major role:

**a)** Internet of Things (IoT) and Massive Sensing

**b)** Holographic Communication and Extended Reality (XR)

**c)** Telemedicine and Mission-Critical Communications

**d)**Vehicular Communications and Autonomous Systems [3],[7],[9].

Table 2 presents a comparative overview of Deep JSCC applications across representative 6G scenarios, highlighting the key requirements, advantages, and the unique challenges associated with each domain.

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**Table 2. Comparative overview of Deep JSCC applications in representative 6G scenarios: key requirements, advantages, and unique challenges [3],[6],[7],[11].**

| Application Domain | Key Requirements | Deep JSCC Advantages | Unique Challenges |
|---|---|---|---|
| IoT and Sensing | Energy efficiency, scalability | Lightweight encoders, adaptive rate control | Power consumption on resource-limited devices |
| XR and Holography | High data rates, low latency | GAN-based perceptual fidelity, OFDM hybrid | Large-scale models, massive data volumes |
| Telemedicine | Ultra-reliability, diagnostic quality | Robust reconstructions, perceptual loss | Error-free performance required |
| Vehicular Systems | Real-time, high mobility | Adaptive redundancy, subms response | Channel impairments (fast fading, Doppler shifts) |

## V. Critical Evaluation of Deep JSCC Architectures

Despite the promising performance of Deep JSCC architectures, they suffer from several critical limitations:

a) Benchmarking Inconsistencies: Studies nowadays use a wide variety of datasets and channel settings, with few standards. This complicates fair performance comparisons and hinders experiment replication.

b) Simplistic Channel Assumptions: Most of the models focus on AWGN channels, which do not really represent 6G conditions. These include high mobility impairments and dignitaries amongst the multipath fading sources that can exist at these frequencies.

c) Neglect of Latency and Efficiency: Evaluations are basic, with PSNR and SSIM the main criteria. Often overlooked, however, latency and model size and inference time constitute crucial factors for 6G.

d) Poor Generalization: Most models are trained on limited datasets and may struggle to recognize unseen image types or adapt to variable channel conditions.

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e) Lack of Interpretability: Deep JSCC remains a black box approach. In safety-critical applications, this lack of transparency can severely limit trust and adoption [12].

## VI. Challenges and Future Directions

(Deep JSCC) shows strong potential for reliable visual communication in future 6G systems, but several open challenges must be addressed before real-world deployment. Recent surveys highlight four major limitations and corresponding research opportunities.

### *a. Computational Complexity*

Deep JSCC models often use large neural networks (CNNs, Transformers, GANs), which demand high processing power and memory, making them ill-suited for IoT and edge devices. Future directions include lightweight architectures, model compression, and neural architecture search (NAS) to maintain performance while reducing complexity.

### *b. Interpretability and Trust*

Deep JSCC is a black box, making its decisions hard to explain, which hinders its use in safety-critical applications like telemedicine and autonomous driving. Future work should focus on integrating explainable AI (XAI) methods to improve the understanding of feature prioritization and redundancy allocation. Deep JSCC is a "black box," making its decisions hard to explain, which hinders its use in safety-critical applications like telemedicine and autonomous driving. Future work should focus on integrating explainable AI (XAI) methods to improve the understanding of feature prioritization and redundancy allocation.

### *c. Generalization and Robustness*

Many models are trained on limited datasets and simple channel models, leading to performance issues in real wireless conditions with mobility, interference, and fading. Future efforts should focus on domain adaptation, meta-learning, and using diverse large-scale datasets to enhance generalization.

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### *d. Standardization and 6G Integration*

Current wireless standards like 5G NR don't natively support Deep JSCC. Future efforts aim to create benchmark datasets, unified evaluation frameworks, and hybrid solutions combining Deep JSCC with classical codes.

### *e. Emerging Opportunities*

Deep JSCC aligns with several promising 6G directions:

- semantic communication.
- green and energy-efficient AI.
- cross-layer optimization.
- and multimodal transmission involving audio, video, and sensor data.[4],[6],[12]

## VI. Conclusion

In summary, the rising demand for data-rich applications has made wireless visual communication a key element of next-generation networks. With 6G aiming for ultra-high data rates, low latency, and the ability to connect numerous devices, effectively transmitting images and videos poses significant challenges. This paper revisits the limitations of traditional separation-based techniques and introduces (Deep JSCC) as a unified solution. By combining compression and error protection in an end-to-end learning framework, Deep JSCC demonstrates potential for meeting 6G's strict requirements. We explored various architectures, including autoencoders and hybrid adaptive schemes, which offer a range of trade-offs in efficiency, robustness, and quality. Practical applications in (IoT),(XR), telemedicine, and autonomous systems showcase Deep JSCC's versatility. However, challenges such as computational complexity, generalization, and interpretability remain. Addressing these issues is crucial for deploying Deep JSCC in real 6G environments.

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