Enhanced Semantic Communication in 6G Networks Using DCGAN

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Abstract. Semantic communication diverges from Shannon's communication theory by prioritizing the semantic essence of data over its step-by-step reconstruction at the receiver's end, signifying its potential to shape the future of mobile communication. This approach aims to address the limitations posed by finite bandwidth in transmitting information for modern, high-volume multimedia applications. Leveraging the integration of AI technology with 6G networks, it provides complete communication systems built on semantic communication concepts. This research focuses on creating an end-to-end picture transmission system based on semantic communication by investigating important design factors that are linked with physical channel features.

To achieve transmission of realistic images from semantically segmented inputs, previously trained DCGAN (Deep Convolutional Generative Adversarial Network) model is used at the target end., trained using COCO-Stuff dataset for both receiver DCGAN (decoder) and transmitter semantic segmentation (encoder). Notably, the study unveils that broadcasting semantic segmentation maps, rather than actual images, across the physical channel yields substantial resource gains, particularly in bandwidth conservation compared to conventional communication methods. Additionally, the research delves into examining the effects of quantization noise and physical channel irregularities on multimedia content transfer facilitated by semantic communication.

Keywords: Semantic Communications · Deep Convolutional Generative Adversarial Network (DCGAN) · Encoder and Decoder

1 Introduction

The progress in wireless sensor networks (WSNs), Internet of Things (IoT), and the increasing volume of multimedia traffic pose sustainability challenges in the administration of communication networks. The complexity amplifies bandwidth and energy demands, urging integration of sustainability measures. Semantic

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communication emerges as a solution, aiming to [9] convey information meaningfully, reducing physical bandwidth. While beneficial for high-bandwidth applications like video streaming, its cost-effectiveness the situation with machine-to-machine (M2M) communication is less clear. However, incorporating semantic communication promises longer operational periods for battery-powered gadgets and less complexity [22].

Traditional communication focused on minimal error transmission based on Shannon's capacity limit. Semantic communication prioritizes conveying intended meaning, [18]often overlooked in traditional systems. For instance, a system proposed for image transmission through mobile channels extracts a semantic map, transmitting only essential information rather than the entire image, thus reducing data volume without compromising quality [3].

DCGAN-Based Semantic Communication System: A DCGAN-based semantic communication system for picture transmission was created employing Polar codes as the channel coding in order to overcome sustainability concerns. [20] Evaluation in various noisy scenarios showed its superior performance over JPEG compression, promising in both human perception and technical efficiency. These findings support its real-world implementation.

The escalating demands on communication networks necessitate sustainable solutions. [1] Semantic communication offers a promising approach by focusing on conveying meaning, not just data, showcasing potential for reducing bandwidth and energy consumption in various applications, with implications for future network designs and sustainability measures.

Polar Codes for Channel Coding: One kind of linear block error-correcting code is the polar code. The code creation process converts the physical channel into virtual outer channels by means of numerous recursive concatenation of a brief kernel code. They are used in the DCGAN-based semantic communication system for channel coding.

2 Objectives

- Create advanced semantic communication systems that prioritize the transmission of data's inherent semantic essence over traditional methods, revolutionizing the way information is exchanged in mobile communication networks.
- Address the urgent bandwidth limitations faced by contemporary high-volume multimedia applications by developing efficient and bandwidth-friendly techniques for data transmission and reconstruction [1].
- Incorporate cutting-edge artificial intelligence technologies into 6G communication networks to enhance the understanding of data semantics and context, enabling more intelligent and context-aware communication.

3 Literature Review

In 2016, the Journal of Circuits and Systems published "Binary phase shift keying digital modulation technique for noiseless and noisy transmission," volume 5, number 3, pages 24–30.

This research investigates Binary Phase Shift Keying (BPSK) Digital Modulation for Noiseless and Noisy Transmission, with an emphasis on (i) constructing a BPSK system, (ii) proving modulation/demodulation using noiseless channels, and (iii) demonstrating the same approach in noisy channels. The study and simulations use a model-based method in Matlab/Simulink to assess the system's efficacy and requirements. However, in noisy transmission channels, mistakes might arise in the demodulated bits, showing the influence of channel noise on the operation [2].

6G white paper on machine learning in wireless communication networks," released in 2020

This white paper investigates the integration of machine learning (ML) into wireless communications, specifically in the context of 6G networks. These networks are set to power societal digital changes by providing ubiquitous, stable, and ultra-fast wireless access for both humans and machines. Recent advances in ML research have sparked new innovations like driverless vehicles and voice assistants, powered by powerful ML models, enormous datasets, and strong computational capabilities.

As the demand for connectivity escalates, innovation within 6G wireless networks becomes imperative. ML tools emerge as pivotal solutions in addressing wireless domain challenges. The paper outlines the envisioned impact of ML on wireless communication systems, highlighting key ML methodologies applicable to wireless networks. It delves into problem-solving aspects across network layers-physical, medium access, and application-using ML techniques. Notably, it explores zero-touch optimization of wireless networks, a compelling facet. Each section concludes by posing crucial research questions pertinent to its scope [13].

I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," Commun. ACM, vol. 63, no. 11, pp. 139–144, 2020:

We can outline a novel approach to training generative models that involves employing an adversarial setup consisting of two models working simultaneously: A generative model, labeled as G, is intended to understand the intrinsic data distribution, whereas a discriminative model, denoted as D, is constructed for the same reason. Tasked with distinguishing between samples originating from the training data and those generated by G. G's training focuses on maximizing D's mistake rate, which results in a minimax game. In the realm of potential functions represented by G and D, a unique solution arises: G replicates the data distribution, while D consistently approaches an output of 1/2. By utilizing multilayer perceptrons to define G and D, the complete system may be trained with backpropagation, eliminating the requirement for Markov chains or approximation inference networks.

Summary: Studied about the Generative adversarial networks

The Mathematical Theory of Communication was published in 1949 by the University of Illinois Press in Champaign.

During the Manhattan Project in the 1940s, rural Anderson County, Tennessee, transformed into Oak Ridge. A research project conducted in Oak Ridge investigated how transitioning from rural to urban land use impacts street tree diversity, soil characteristics, and nutrient dynamics. Of 607 street trees across five main roads, Acer rubrum (21.91%) and Pyrus calleryana (19.93%) were predominant. Chemical soil properties notably influenced tree performance, while soil characteristics varied between streets but not due to traffic. Seasonal differences in soil microbial biomass and nutrient levels were observed.

4 Proposed Method

Shannon's theory served as the inspiration for the three-layered theoretical model that forms the foundation of the Semantic Communication-Based Image Transmission System's design. Positioned within the semantic layer are the semantic encoder and decoder components. [10]managing semantic feature extraction and interpretation using a shared knowledge base. The encoder interprets the message's intent, while the decoder extracts meaning from received semantic symbols through mutual knowledge [14].

The physical layer, below the semantic layer, handles bit-level transmission and channel data optimization. Above, the application layer manages task-specific aspects of incoming messages, involving classification, object detection, and scene prediction [21].

The system leverages the COCO dataset as its shared knowledge base, while the COCOStuff subset aids in pre-training the DCGAN. This repository encompasses images for object detection and captioning, featuring 20 pre-trained semantic object classes for the experiment's GAN [15] (Fig. 1).

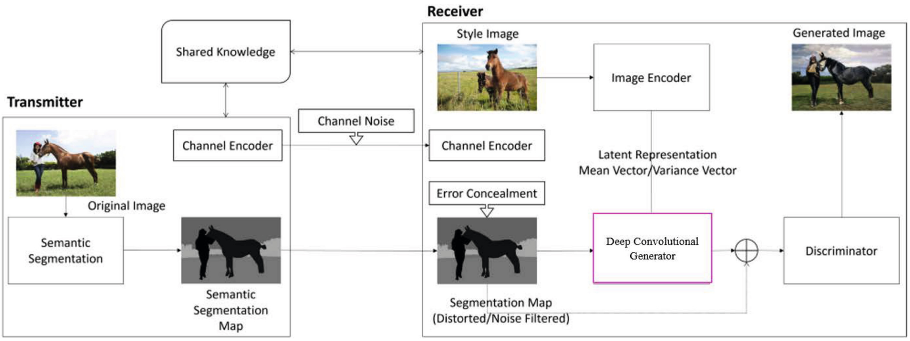

Fig. 1. Proposed Method.

Employing data from the aforementioned dataset, the study generates segmented semantic maps, focusing on ten representative images showcasing diverse subjects. [11] Classification at the receiver is a task within the application layer, categorizing objects based on the GAN's training.

Losses are computed and fed back through the system during the learning process, with each epoch improving both the generator and discriminator more. [12] The discriminator's goal is to improve the value function V(D,G) by accurately categorizing actual pictures (where D(s) approaches 1) and decreasing the classification of fraudulent images. [16] The generator aims to deceive the discriminator into thinking that the images are real, so that there is a lower chance that the discriminator will accurately identify them as created (Table 1).

Table 1. Channel Decoding Specifications

S.No	Parameter	Value
1.	Channel n/Decoder	Polar Codes
2.	Information Bits	2048
3.	Codeword Bits	4096
4.	Code Rate	1/2
5.	Modulation	BPSK
6.	Bits per symbol	2
7.	Demaping Method	Log-liklihood ratios
8.	Channel	AWGN

Polar codes, indicated as PC(M, L), have the power to convert physical channels into dependable or unreliable virtual channels, especially as the code length approaches infinity. For example, a polar code with parameters M = 8192 and L = 4096 is modulated with Binary Phase Shift Keying (BPSK) over an Additive White Gaussian Noise (AWGN) channel to achieve a required Eb/No ratio of 2.5 dB. The receiver's decoder then uses the received noisy Log-Likelihood Ratios (LLRs) to construct approximation codewords, using the suggested practical code validation processes included into the semantic communication system.

4.1 Advantages

- In line with semantic communication principles, the project focuses on conveying the semantic substance of data rather than step-by-step reconstruction. [17] Transferring more significant information is made possible by this prioritizing, particularly when dealing with high-volume multimedia applications [7].
- Significant resource savings are achieved by the initiative, especially in terms of bandwidth conservation, by broadcasting semantic segmentation maps across the physical channel rather than real pictures. [4] This is a significant benefit for resolving the issues caused by current communication networks' limited capacity [19].

– To facilitate the transmission of realistic images from semantically segmented inputs, a pre-trained DCGAN network is used on both the transmitter encoder and the receiver decoder. This method efficiently reduces data consumption while retaining the quality of delivered photographs [6].

5 Results

Fig. 2. The input picture refers to the original image intended for transmission, which serves as the starting point for future processing processes.

The project effectively illustrates the efficient use of DCGAN-enabled enhanced semantic communication in 6G communications networks. [8] Semantically segmenting the input image, which generates a semantically segmented image displaying important features. Using a pre-trained DCGAN network, the system leverages semantic segmentation to generate a realistic output image, demonstrating the potential for communicating important information with less input. The project's success is attributed to the integrated three-layer model, which is in accordance with Shannon's theory and efficiently handles bit-level transmission, task-specific components, and semantic essence prioritizing. [5] Overall, these results emphasize the advantages of semantic communication, especially its ability to minimize bandwidth, and incorporate AI technology, making it a viable option for the next-generation mobile communication networks (see Figs. 2, 3, 4, 5).

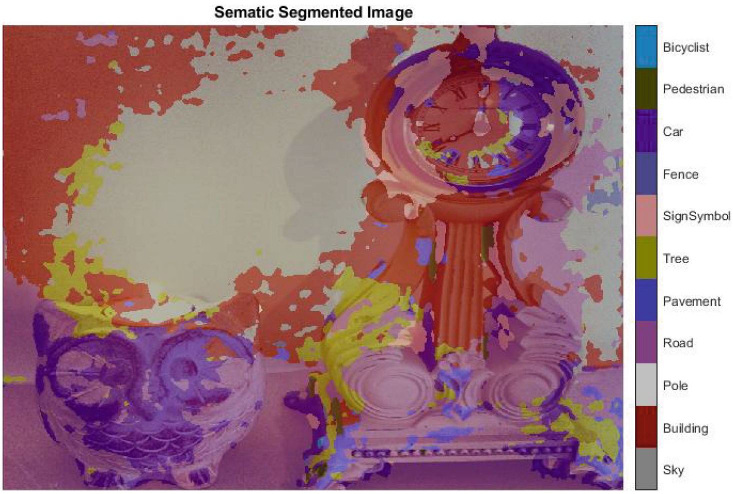

Fig. 3. Semantic Segmented Image. This image is the output of the semantic segmentation, which involves creating a semantic map and extracting the features which are essential.

Fig. 4. Generated Output Image. The DCGAN network tries to produce an image which is close to the actual image that has to be transmitted.

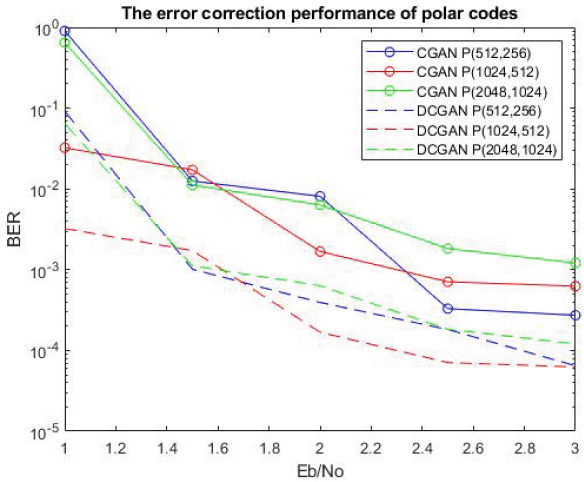

Fig. 5. The Polar codes error correction capability demonstrates the relationship between signal-to-noise ratio and capacity to repair mistakes.

6 Conclusion

In conclusion, by implementing semantic essence prior to step-by-step reconstruction, the proposed Enhanced Semantic Communication in 6G Networks Using DCGAN presents an extensive approach to transform mobile communication networks. Using a three-layer paradigm built around Shannon's theory, the system employs an application layer for handling task-specific characteristics, a physical layer that transmits information at the bit-level, and a semantic encoder and decoder for feature extraction. The integration of pre-training DCGAN with the COCO dataset and COCOStuff subset demonstrates an excellent foundation for object detection and captioning. The system's efficiency is demonstrated by the generation of segmented semantic maps and the classification that follows at the application layer's receiver. Polar Codes for channel encoding/decoding are a viable and optimal solution for both dependable and unreliable virtual channels. Through each epoch, the system is refined by learning, which is powered by the min-max formulation for the discriminator and generator. The discriminator attempts to correctly classify genuine images, whereas the generator attempts to fool by producing convincing images. Robustness, great efficiency, and the possibility of deep-level implementation are some benefits of the suggested approach.

According to the research, by fusing technology and artificial intelligence, semantic communication in 6G networks has the ability to completely transform the transmission of multimedia material. Semantic segmentation maps are an effective way to conserve resources, especially bandwidth. This is demonstrated by their adoption. An in-depth understanding of how semantic communication affects multimedia material transfer is made possible by examining issues like quantization noise.

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