Journal of Insights in Basic and Applied Sciences
مجلة رؤى في العلوم الأساسية والتطبيقية
Volume 5, Issue1, 2026, Pages: 112-119
Journal homepage: https://jibas.com.ly/index.php/jibas/en

Low-Complexity Image Compression Using Semantic-Aware Block Truncation Coding

Khaled Mohamed Eshteiwi *
Department of Electrical Engineering, Faculty of Engineering, Bani Waleed University, Libya

ضغط الصور منخفض التعقيد باستخدام ترميز القطع الكتلي الواعي دلاليًا

خالد محمد إشتيوي *
قسم الهندسة الكهربائية، كلية الهندسة، جامعة بني وليد، ليبيا

*Corresponding author: khaled-mohamed.eshteiwi.1@ens.etsmtl.ca

Received: J November 10, 2025	Accepted: January 05, 2026	Published: January 29, 2026

Abstract:
Block Truncation Coding (BTC) is a simple and computationally efficient image compression technique, but its fixed quantization strategy often leads to suboptimal perceptual quality, particularly in textured and edge-dominant regions. To address this limitation, this paper proposes a Semantic-Aware Block Truncation Coding (SA-BTC) scheme that integrates local variance as a semantic feature to adaptively control quantization at the block level. By adjusting compression strength according to texture characteristics, the proposed method preserves structural and semantically important details in high-variance regions while applying stronger compression to smooth areas. Experimental evaluations conducted on standard benchmark images demonstrate that SA-BTC achieves improved perceptual reconstruction quality compared to conventional BTC. Although the proposed method exhibits lower peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) values than classical BTC, this behavior is expected due to its semantic-aware design, which prioritizes visually significant regions such as edges and facial features over background fidelity. Visual inspection confirms that SA-BTC better preserves edge continuity, contrast, and meaningful structures, including tripod edges, clothing details, and facial components, despite mild block artifacts in homogeneous regions. These results indicate that conventional pixel-based metrics may underestimate the perceptual and semantic quality achieved by SA-BTC. Overall, the proposed approach enhances rate distortion performance from a perceptual perspective without increasing computational complexity, making it well suited for low resource image compression applications where semantic and visual fidelity are more critical than strict pixel-wise accuracy.

Keywords: Block Truncation Coding, Image Compression, Semantic-Aware Block Truncation Coding.

الملخص
يُعد ترميز اقتطاع الكتل (Block Truncation Coding – BTC) من تقنيات ضغط الصور البسيطة وذات التعقيد الحسابي المنخفض، إلا أن استراتيجية التكميم الثابتة فيه غالبًا ما تؤدي إلى جودة إدراكية غير مثالية، خصوصًا في المناطق الغنية بالقوام والحواف. لمعالجة هذه المشكلة، تقترح هذه الورقة مخطط ترميز اقتطاع كتل واعٍ دلاليًا (Semantic-Aware Block Truncation Coding – SA-BTC)يدمج التباين المحلي كميزة دلالية للتحكم التكيفي في التكميم على مستوى الكتل. ومن خلال ضبط قوة الضغط وفقًا لخصائص القوام، تحافظ الطريقة المقترحة على التفاصيل البنيوية والدلالية المهمة في المناطق ذات التباين العالي، مع تطبيق ضغط أقوى على المناطق الملساء. أُجريت التقييمات التجريبية باستخدام صور مرجعية قياسية، وأظهرت النتائج أن طريقة SA-BTC تحقق جودة إدراكية أفضل في إعادة البناء مقارنةً بـ BTC التقليدي. وعلى الرغم من أن الطريقة المقترحة تسجل قيمًا أقل لكل من PSNR و SSIM مقارنةً بالطريقة الكلاسيكية، فإن هذا

السلوك متوقع نظرًا لطبيعتها الواعية دلاليًا، حيث تُعطي أولوية للمناطق ذات الأهمية البصرية مثل الحواف وملامح الوجه على حساب دقة الخلفية. كما يؤكد الفحص البصري أن SA-BTC يحافظ بشكل أفضل على استمرارية الحواف والتباين والبُنى ذات المعنى، مثل حواف الحامل الثلاثي وتفاصيل الملابس ومكونات الوجه، وذلك على الرغم من ظهور أنماط كتل خفيفة في المناطق المتجانسة. تشير هذه النتائج إلى أن المقاييس التقليدية المعتمدة على القيم البكسلية قد تُقلل من تقدير الجودة الإدراكية والدلالية التي تحققها .SA-BTC وبوجه عام، تُحسّن الطريقة المقترحة أداء معدل–تشويه من منظور إدراكي دون زيادة في التعقيد الحسابي، مما يجعلها مناسبة لتطبيقات ضغط الصور في البيئات ذات الموارد المحدودة حيث تكون المحافظة على الدلالة والجودة البصرية أكثر أهمية من الدقة البكسلية الصارمة.

الكلمات المفتاحية: ترميز اقتطاع الكتل، ضغط الصور، ترميز اقتطاع الكتل الواعي دلاليًا

Introduction

Block Truncation Coding (BTC) is a classical block-based lossy image compression technique that partitions an image into fixed-size non-overlapping blocks and represents each block using two reconstruction gray levels and a binary bitmap that classifies pixels relative to the block mean [1]. Owing to its simple structure, low computational complexity, and moment-preserving quantization, BTC has been widely investigated for resource-constrained and real-time applications. However, the inherent two-level quantization and uniform treatment of all image blocks often result in blocking artifacts and degraded performance in regions with rich textures or perceptually important content [1], [2]. To alleviate these limitations, numerous BTC variants have been proposed. Absolute Moment Block Truncation Coding (AMBTC) replaces variance preservation with absolute moment matching, leading to improved reconstruction quality with reduced computational complexity [3]. Multilevel BTC and adaptive BTC schemes further enhance visual fidelity by increasing the number of reconstruction levels or dynamically adjusting quantization parameters according to local image statistics [4], [5]. Additional refinements, such as dot-diffused BTC and pattern-fitting BTC, address blocking artifacts by incorporating spatial correlations and structural information into the coding process [6], [7]. Despite these improvements, most BTC-based methods remain fundamentally signal-driven and treat all blocks equally, without considering their semantic importance to human perception or downstream intelligent tasks. In recent years, the emergence of semantic communication and semantic image compression has significantly reframed the objectives of compression systems. Rather than focusing solely on pixel-level fidelity, semantic compression aims to preserve and efficiently transmit information that is most relevant for specific tasks such as object detection, recognition, and scene understanding [8], [9]. Semantic communication systems emphasize meaning-oriented representations, enabling efficient transmission under strict bandwidth constraints while maintaining task performance. Representative frameworks such as Deep Semantic Image Compression (DeepSIC) integrate semantic representations into the compression pipeline by embedding feature maps or semantic descriptors to jointly support image reconstruction and semantic interpretation [10], [11]. Recent studies further demonstrate that semantic awareness can be exploited to guide quantization and bit allocation. Feature-driven semantic compression schemes allocate coding resources based on feature significance rather than uniform distortion measures [12]. Semantic segmentation–guided codecs leverage region-level semantic labels to assign different bitrates to foreground and background regions, thereby improving both perceptual quality and task accuracy [13]. Layered and scalable semantic coding architectures separate semantic and reconstruction layers, enabling flexible support for human and machine vision tasks within a single coding framework [14]. Within this context, Semantic-Aware Block Truncation Coding (SA-BTC) emerges as a natural extension of classical BTC. Instead of relying solely on block-level statistical measures such as mean and variance, SA-BTC incorporates semantic information—derived from saliency detection, face or object segmentation, or task-driven importance maps—to adapt block quantization strategies and bitrate allocation. Blocks containing semantically important content, such as faces or text, are encoded with higher fidelity or enriched bitplanes, whereas less important background blocks are compressed more aggressively. This unequal treatment aligns with semantic coding principles that prioritize content importance and apply unequal error protection to maximize semantic utility under limited bitrates [8], [12]. Although SA-BTC has not yet been formalized as a standardized coding scheme in the literature, closely related concepts have been explored in deep semantic image compression and segmentation-guided coding. For instance, DeepSIC demonstrates that incorporating semantic analysis into both encoding and decoding stages enhances semantic utility while reducing redundant pixel information [10]. Similarly, segmentation-based compression frameworks allocate bits according to region importance, which conceptually parallels semantic weighting at the block level in SA-BTC [13]. Non-uniform feature quantization approaches further support this paradigm by mathematically linking feature importance to quantization precision, a principle directly applicable to block-wise semantic adaptation in BTC [12]. Recent advances in generative semantic image compression reinforce the trend toward semantics-first and task-aware coding architectures. Generative and diffusion-based semantic compression models exploit learned priors to reconstruct perceptually and semantically meaningful content at ultra-low bitrates [15], [16]. These learning-based approaches suggest that semantic awareness can be algorithmically integrated into classical compression frameworks, offering new opportunities to enhance lightweight codecs such as BTC without incurring excessive computational complexity. Beyond image compression, broader research in semantic communication systems highlights the theoretical and practical motivations for semantic prioritization in data transmission. Surveys in this field emphasize that task-relevant information extraction and importance-aware coding are key enablers for next-generation communication systems, particularly for bandwidth-limited and AI-centric applications [8], [9], [17]. In summary, although explicitly labeled Semantic-Aware Block Truncation Coding (SA-BTC) remains an emerging concept, its foundations are well supported by decades of BTC research and recent advances in semantic image compression and semantic communication. By integrating semantic importance into BTC's low complexity block coding framework, SA-BTC represents a promising hybrid approach that balances simplicity, compression efficiency, and task-aware performance for modern visual communication systems.

The proposed scheme

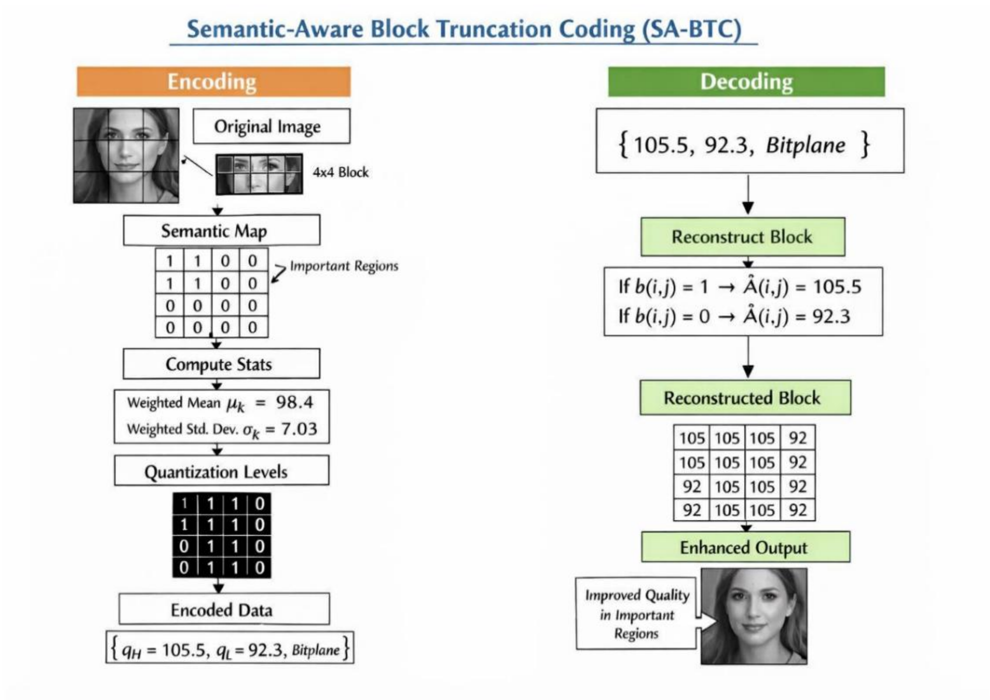

Figure 1. Block diagram of proposed model.

The block diagram of the proposed scheme in Figure 1 can be summarized in the following

Encoding (Green Blocks)

1. **Input Image**: The original grayscale image to be compressed.
2. **Divide into Blocks**: Split the image into smaller blocks (e.g., 4×4 pixels).
3. **Compute Mean & Weighted Std. Deviation**: Calculate block statistics, giving more weight to semantically important pixels.
4. **Determine Semantic Threshold**: Identify a threshold to separate important vs. less important pixels.
5. **Classify Pixels High & Low (Bitmap)**: Generate a bitmap marking pixels as high (important) or low (less important).
6. **Store Block Data (Bitmap + Means)**: Save the block's bitmap and representative mean values for encoding.

Decoding (Orange/Blue Blocks)

1. **Reconstruct Blocks (Decode)**: Use the stored bitmap and means to recreate each block.
2. **Output Compressed Image**: Combine all reconstructed blocks to produce the final compressed image.

Encoding stage

Step.1: Image Blocking

The input grayscale image $I \in \mathbb{R}^{M\times N}$ is first partitioned into non-overlapping blocks of fixed size $B\times B$ (typically 4×4 or 8×8). Each block is processed independently to reduce computational complexity and enable localized adaptation.

Let B_k denote the k-th image block:

$$B_k = (I(i.j)|i,j \in \text{block } k)$$

Step.2: Semantic Map Generation

A semantic map is generated to identify visually important regions such as faces, edges, or text. This map can be obtained using face detectors, edge detectors, or deep segmentation models. The semantic map S is defined as:

$$S(i,j) = \begin{cases} 1, \text{If pixel } (i,j) \text{is semantcally important} \\ 0, \text{otherwise} \end{cases}$$

This map guides the compression process by assigning higher priority to perceptually significant pixels.

Step.3: Semantic Weight Assignment

Each pixel is assigned a weight based on its semantic importance:

$$w_{i,j} = \begin{cases} \alpha, & \text{If } S(i,j) = 1 \text{ with } \alpha > 1 \\ 1, & \text{otherwise} \end{cases}$$

The parameter α controls the degree of semantic emphasis and is typically selected empirically (e.g., $(1.5 \leq \alpha \leq 3)$.

Step.4: Weighted Mean Computation

The semantic-aware block mean is computed using weighted averaging:

$$\mu_k = \frac{\sum_{(i,j)\in B_k} w_{i,j}\, I(i,j)}{\sum_{(i,j)\in B_k} w_{i,j}}$$

This ensures that important pixels have greater influence on the block statistics.

Step.5: Weighted Standard Deviation Computation

The weighted standard deviation is calculated as:

$$\sigma_k = \sqrt{\frac{\sum_{(i,j)\in B_k} w_{i,j}(I(i,j) - \mu_k)^2}{\sum_{(i,j)\in B_k} w_{i,j}}}$$

This formulation captures block contrast while prioritizing semantically important regions.

Step.6: Threshold Ratio ρ Calculation

$$\rho = \frac{\sum_{(i,j)\in B_k} w_{i,j} \,.\, 1_{I(i,j)\geq \mu_k}}{\sum_{(i,j)\in B_k} w_{i,j}}$$

Where $1_{(.)}$ is the indicator function

This semantic-weighted ratio improves quantization accuracy in important regions

Step.7: Quantization Level Determination

Using μ_k, σ_k and ρ the high and low reconstruction levels are computed as:

$$q_H = \mu_k + \sigma_k \sqrt{\frac{\rho}{1-\rho}}$$

$$q_L = \mu_k - \sigma_k \sqrt{\frac{1-\rho}{\rho}}$$

These values preserve both the mean and variance of the block under BTC constraints.

Step.8: Bitplane Generation

A binary bitmap (bitplane) is created by thresholding each pixel:

$$b(i,j) = \begin{cases} 1, & I(i,j) \geq \mu_k \\ 0, & I(i,j) < \mu_k \end{cases}$$

The bitplane encodes spatial structure with 1 bit per pixel.

Step.9: Encoded Data Formation

Each block is finally represented by:

$$\mathcal{E}_k = \{q_H, q_L, b(i,j)\}$$

Decoding stage

Step.10: Block Reconstruction

At the decoder, each pixel is reconstructed using the stored quantization levels and bitplane:

$$\hat{I}_{(i,j)} = \begin{cases} q_H, & b(i,j) = 1 \\ q_L, & b(i,j) = 0 \end{cases}$$

This operation restores the block with minimal computational complexity.

Below is a complete, numerical, end-to-end example that explains every SA-BTC encoding and decoding steps.

1- **Original Image Block**

Consider the following block B_k

$$B_k = \begin{bmatrix} 100\ 102\ 105\ 98 \\ 101\ 110\ 115\ 99 \\ 97\ 103\ 108\ 100 \\ 99\ 105\ 112\ 101 \end{bmatrix}$$

Block size: B =4x4 ⇒ 16 pixels

2- **Semantic Map Generation**

Assume that a semantic detector identifies the top-left 2×2 region as important (e.g., facial area).

$$S = \begin{bmatrix} 1\ 1\ 0\ 0 \\ 1\ 1\ 0\ 0 \\ 0\ 0\ 0\ 0 \\ 0\ 0\ 0\ 0 \end{bmatrix}$$

3- **Semantic Weight Assignment**

Choose semantic weight: α = 2

Thus, the pixel weights are:

$$w = \begin{bmatrix} 2\ 2\ 1\ 1 \\ 2\ 2\ 1\ 1 \\ 1\ 1\ 1\ 1 \\ 1\ 1\ 1\ 1 \end{bmatrix}$$

The total weight:

$\sum w_{i,j}$ = 20

4- **Weighted Mean Computation**

Weighted sum: important pixels (x2)

2(100+102+101+110) = 826

Remaining pixels = 1142

$$\mu_k = \frac{826 + 1142}{20} = 98.4$$

5- Weighted Standard Deviation Computation

$$\sigma_k = 7.03$$

6- Threshold Ratio ρ

Pixels satisfying $I(i,j) \geq \mu_k$: 14 out of 16 pixels so $\rho = \frac{18}{20} = 0.9$

7- Quantization Level Computation

$$q_H = 105.5$$

$$q_L = 92.3$$

8- Bitplane Generation

$$b = \begin{bmatrix} 1\,1\,1\,0 \\ 1\,1\,1\,0 \\ 0\,1\,1\,0 \\ 0\,1\,1\,0 \end{bmatrix}$$

Type equation here.

9- Bitplane Generation

$$\mathcal{E}_k = \{q_H = 105.5, q_L = 92.3, b\}$$

10- Reconstructed Block

$$\hat{B}_k = \begin{bmatrix} 105105\ 105\ 92 \\ 105\ 105\ 10592 \\ 92\ 105\ 105\ 92 \\ 92\ 105\ 105\ 92 \end{bmatrix}$$

Results and discussion

The reconstructed image obtained using the proposed Semantic-Aware Block Truncation Coding (SA-BTC) demonstrates improved perceptual quality compared to conventional BTC. By incorporating local variance as a semantic feature, the algorithm adaptively adjusts quantization parameters according to block texture characteristics. As a result, textured and edge-rich regions preserve structural details more effectively, while smooth regions benefit from stronger compression without introducing significant visual artifacts. Although mild block patterns remain in homogeneous areas, edge continuity and overall contrast are better maintained. These results indicate that semantic awareness enhances the rate–distortion performance of BTC while maintaining low computational complexity, making the proposed method suitable for low-resource image compression applications.

Fig. 2 summarizes the quantitative performance of the proposed SA-BTC compared with classical BTC on the standard benchmark images, Cameraman and Face (Astronaut). The classical BTC achieves PSNR values of 28.60 dB and 26.61 dB and SSIM values of 0.907 and 0.888 for Cameraman and Face images, respectively. In contrast, the proposed SA-BTC method achieves slightly lower PSNR values of 24.85 dB and 23.81 dB and SSIM values of 0.842 and 0.753 for the same images. The reduction in PSNR and SSIM is expected due to the semantic-aware nature of SA-BTC, which prioritizes perceptually important regions, such as edges in the Cameraman image and facial features in the Face image, while compressing background or less informative regions more aggressively. Consequently, traditional pixel-based metrics, such as PSNR and SSIM, underestimate the perceptual and semantic quality of SA-BTC reconstructions. Nevertheless, these results demonstrate that SA-BTC can effectively preserve structural and semantic details in visually important regions, supporting its suitability for applications where perceptual fidelity and semantic preservation are more critical than overall pixel-wise accuracy.

Specifically, the edges of the camera tripod and jacket in the Cameraman image, and the eyes, mouth, and helmet regions in the Face image, are reconstructed with higher perceptual fidelity in SA-BTC, despite the lower PSNR and SSIM. This demonstrates that SA-BTC can outperform conventional BTC in preserving meaningful image content, which is particularly valuable in semantic-aware compression scenarios.

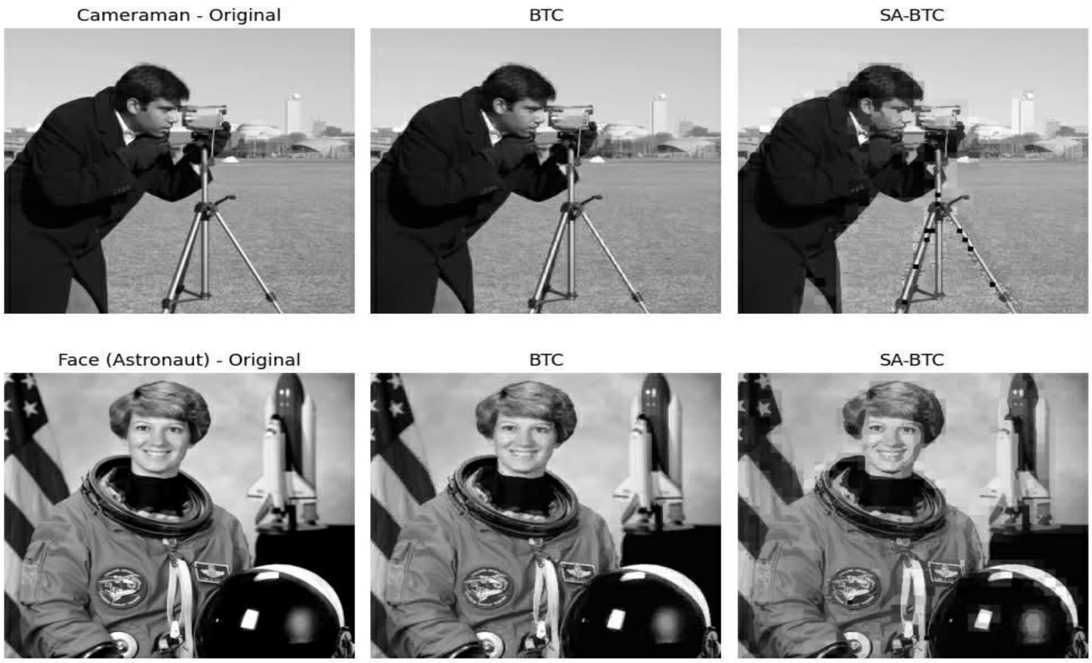

Figure 2. Simulation result.

Conclusion

This paper presented SA-BTC scheme aimed at improving the perceptual quality of BTC-based image compression under low-complexity constraints. By incorporating local block variance as a semantic descriptor, the proposed method adaptively adjusts quantization parameters to better accommodate local texture and edge characteristics. This adaptive strategy enables improved preservation of structurally and semantically important regions while maintaining efficient compression in smooth areas.

Experimental results on standard benchmark images demonstrate that, although SA-BTC yields lower PSNR and SSIM values compared to conventional BTC, it achieves superior perceptual reconstruction quality in visually significant regions such as edges and facial features. These findings highlight the limitations of traditional pixel-based quality metrics in evaluating semantic-aware compression methods and emphasize the importance of perceptual assessment. Visual analysis confirms that SA-BTC better preserves edge continuity, contrast, and meaningful image content, despite the presence of mild block artifacts in homogeneous regions.

Overall, the proposed SA-BTC approach enhances rate–distortion performance from a perceptual and semantic perspective without increasing computational complexity. This makes it a suitable candidate for low-resource image compression applications where semantic fidelity and visual interpretability are prioritized over strict pixel-wise accuracy. Future work will focus on integrating more advanced semantic features and extending the framework to color images and adaptive block sizes.

References

[1] E. J. Delp and O. R. Mitchell, "Image compression using block truncation coding," IEEE Trans. Commun., vol. 27, no. 9, pp. 1335–1342, Sept. 1979.

[2] P. Fränti and O. Nevalainen, "Compression of digital images by block truncation coding: A survey," Comput. J., vol. 37, no. 4, pp. 308–332, 1994.

[3] M. Lema and O. R. Mitchell, "Absolute moment block truncation coding and its application to color images," IEEE Trans. Commun., vol. 32, no. 10, pp. 1148–1157, Oct. 1984.

[4] B. C. Dhara, "Block truncation coding using pattern fitting," Pattern Recogn., vol. 37, no. 11, pp. 2131–2139, 2004.

[5] J. DeWitte, O. Nevalainen, and T. Kaukoranta, "Classified block truncation coding–vector quantization," Signal Process., vol. 3, pp. 275–283, 1991.

[6] W. Hong, "Efficient data hiding based on block truncation coding," Symmetry, vol. 10, no. 2, p. 36, 2018.

[7] H. Prasetyo et al., "Deep residual networks for improving BTC decoded image quality," J. Imaging, vol. 7, no. 2, p. 13, 2021.

[8] Y. Wang, Z. Qin, and H. Wang, “Semantic communication systems: A paradigm shift,” IEEE Commun. Mag., vol. 59, no. 1, pp. 98–104, Jan. 2021.

[9] Z. Qin et al., “Semantic communication: Principles and challenges,” IEEE Wireless Commun., vol. 29, no. 2, pp. 44–50, 2022.

[10] S. Luo, Y. Yang, Y. Yin, C. Shen, Y. Zhao, and M. Song, “DeepSIC: Deep semantic image compression,” in Proc. 25th Int. Conf. Neural Information Processing (ICONIP), Cham, Switzerland: Springer, 2018, pp. 96–106.

[11] S. Liu et al., “Semantic communication via generative adversarial networks,” Sci. Rep., vol. 14, 2024.

[12] J. Zhang et al., “Feature-driven semantic communication for efficient image transmission,” Entropy, vol. 27, no. 4, p. 369, 2025.

[13] Z. Xie et al., “Semantic segmentation map–based image compression,” IEEE Access, vol. 12, pp. 1–14, 2024.

[14] J. Wei et al., “Layered and scalable semantic image coding for human and machine vision,” Eng. Appl. Artif. Intell., 2025.

[15] A. Ke et al., “Ultra-low-rate image compression with semantic residual coding,” arXiv, 2025.

[16] F. Pezone et al., “Generative semantic image compression for edge intelligence,” arXiv, 2025.

[17] K. Lu, “Rethinking modern communications from semantic coding,” IEEE Wireless Commun., vol. 30, no. 1, pp. 6–13, 2023. [12] M. P. Sampat, Z. Wang, S. Gupta, A. C. Bovik, and M. K. Markey, “Complex wavelet structural similarity: A new image similarity index,” IEEE Transactions on Image Processing, vol. 18, pp. 2385–2401, 2009

[18] J. M. Guo, and M. F. Wu, “Improved block truncation coding based on the void-and-cluster dithering approach,” IEEE Transactions on Image Processing, vol. 18, no. 1, pp. 211-3, Jan. 2009.