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Image Compression Using Elimination and Dynamic Rules

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Abstract

This study proposes a method for developing the Triangular Inequality Elimination (TIE) rule and applying it in image compression based on block quantization. The study employed a dynamic rule to enhance and refine the TIE method. Applying the dynamic rule to the TIE algorithm reduces the computational complexity during the compression (coding-decoding) process, speeds up execution and transmission, and eliminates the need for large storage spaces. The dynamic rule is useful because it changes blocks close to the reference block during each attempt (S) to find the smallest number of blocks closest to the reference block. These blocks were then placed in a set. The higher the blocks in the set, the higher the image quality is at the expense of the compression ratio. The results of the dynamic rule that modifies the TIE algorithm are high compression ratios, quick implementation, low storage space for the image, and good reconstructed image quality. In other words, the suggested method, Triangular Inequality Elimination with Dynamic Rules (D-TIE), will significantly reduce the time required for matching searches; therefore, it is the least computationally demanding.

Keywords: Image compression, Triangular inequality elimination, Dynamic rule.

ضغط الصور باستخدام قواعد الحذف والديناميكيه

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الخلاصة

في هذه الدراسة تم اقتراح طريقة لتطوير قاعدة الازالة المثلثية (TIE) واستخدامها في ضغط بيانات الصور اعتمادا على طريقة تكميم الكتل. الدراسة استخدمت القاعدة الديناميكية لتحسين وتطوير طريقة (TIE) حيث ان تطبيق القاعدة الديناميكية على خوارزمية (TIE) تعمل على تقليل التعقيد الحسابي اثناء عملية الضغط متمثلة بالتشفير واعادة فك التشفير وتسريع عملية التنفيذ والارسال بالاضافة الى عدم الحاجة الى مساحات خزن كبيرة. وان الفائدة من استخدام القاعدة الديناميكية انها تعمل على تبديل الكتل القريبة للمرجع في كل محاولة (S) لايجاد اصغر عدد من الكتل الاقرب جدا الى كتلة المرجع بعدها يضع هذه الكتل في مجموعة نهائية. كلما كانت عدد الكتل في المجموعة اكبر كانت جودة الصوره اعلى على حساب نسبة الضغط. النتائج التي تم الحصول عليها من القاعدة الديناميكية التي تُعدِّل خوارزمية TIE هي نسب ضغط عالية، وسرعة في التنفيذ، ومساحة تخزين للصوره منخفضه، وجودة جيدة للصوره المسترجعه. بمعنى آخر،

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ستُقلِّل الطريقة المقترحة، وهي إزالة التباين المثلثي باستخدام القواعد الديناميكية (D–TIE)، زمن عمليات البحث للمُطابقة بشكل كبير, وبالتالي، فهي الأقل صعوبة حسابيًا.

1. Introduction

Owing to the digital revolution that has unfolded in the last few years, there has arisen a critical necessity of coming up with digital image processing methods for various practical [1], scientific [2], engineering [3], and industrial applications in various fields of life, such as medicine [4], art [5], astronomy [6], data analysis [7], satellite image enhancement [8], restoration, and compression [9], [10], as well as remote sensing [11], [12], [13], and [14].
The most significant challenges in digital image processing are the large size of high-resolution color images, the large size of images, and the high level of detail in highly detailed maps. Storing and transmitting many of these images on the internet requires a significant amount of memory and considerable [15]. This requires developing compression methods for image and digital data to increase transmission speed and significantly reduce storage space [16].

The proposed method increases transmission speed and storage space, and reduces calculations, making it more efficient than the vector quantization method. This is because there is no need to search through the codebook, and no need to generate and send the codebook, which consists of many blocks, to achieve high image quality. In the proposed method, only the reference blocks are sent or stored. As a result, the proposed method improved the efficiency of transform-based image encoding using the Triangular Inequality Elimination (TIE) rule over the vector quantization method.

2. Block Quantization

Several image compression techniques have emerged based on Block Quantization (BQ), which involves dividing images into small, equal-sized blocks. A compression technique was then applied to each block. These techniques include Vector Quantization (VQ), developed by Y. Linde, A. Buzo, and R. M. Gray [17]; the Discrete Cosine Transform (DCT) [18]; k-means clustering [19]; and other BQ-based techniques [20]. These techniques have helped reduce file sizes and transmission speeds while maintaining high image quality and improving the efficiency of compression techniques.

VQ is one of the Block Quantization methods in digital image compression. It works by using a large number of blocks and a finite set of blocks (i.e., a codebook) to compress the data, such as images [21], [22], which maps an image's blocks from a large number of blocks, a long vector space, into a smaller set. There are three steps in describing VQ: The initial step is to create the codebook, the second step is coding, and the last step is decoding. The advantages of VQ include a high compression ratio and a simple decoding step; however, it also has disadvantages, such as increased computational complexity and the fact that it is a lossy method [23], [24]. To enhance the quality of image decoding, a large memory space is required for storing the codebook [25]. If the codebook is large, the search time will increase, and the encoding step will lag because each input vector will be compared to all blocks in the codebook [26]. Additionally, the reliance on a large codebook can lead to inefficiencies in both encoding and decoding processes, making it less suitable for real-time applications [27], [28], [29]. As a result, while this method may offer advantages in certain contexts, careful consideration must be given to its limitations when selecting an appropriate coding strategy.

3. Triangular Inequality Elimination Theorem:

The Triangle Inequality Elimination Theorem states that the sum of the lengths of two sides of a triangle is always greater than the length of the third. Where, L1+L2 > L3, L1+L3 > L2, L2+L3 > L1. The TIE algorithm is defined as equation 1:

$TIE = d(C_j, C_i) < 2 \times d(C_j, x)$..... (1)

Where the value of C_j which is nearest to x value [30], [31].

In this study, to improve the performance of block quantization, the TIE algorithm was employed to reduce search time and simplify the search process, resulting in more than 50% computational savings in image coding. However, the TIE algorithm's efficiency depends on the continuous property of an input image. Therefore, the description of the TIE algorithm in block coding can be mentioned as equation 2:

$TIE = Dis(C_i, C_j) < 2 \times Dis(C_i, C_r) \ldots\ldots$ (2)

Where Cj represents all the image blocks, and Cr represents the block nearest to the reference block Ci, this equation significantly reduces the search time.

4. The Dynamic Rule -TIE Algorithm (D-TIE):

The study introduces the dynamic rule to enhance the performance of the TIE algorithm. The dynamic rule was applied to all blocks in the original image. The use of the TIE algorithm with the dynamic rule is clarified in this example.

C_1	C_2	C_3	… … … … … … …	C_j

Image's blocks

1. Using the TIE algorithm, let C1 be the reference, and C2 be the nearest to C1.

$$Dis(C_j, C_1) < 2 \times Dis(C_2, C_1)$$

C_5	C_{19}	C_{11}	C_7	… … …	C_k

Set S1, *k<j*

2. Using the TIE algorithm, let C1 be the reference, and C5 be the nearest to C1.

$$Dis(C_k, C_1) < 2 \times Dis(C_5, C_1)$$

C_{11}	C_7	C_5	… …	C_m

Reset S2, *m<k<j*

:

:

And so on... one can continue to find S3 and S4 according to the required speed and quality.

3. Apply the above steps to the other block, which is not included in any final set, using it as an additional reference.

This example can be described by following the steps. The first step is to select *C*1 as the reference and let C2 be the block nearest to *C1*. The second step is to compute the distortion between *Cj* and the reference C1 to generate the first set S1 of blocks nearest to the reference *C1*. In this case, there are k blocks within the first set whose distortions are less than 2 × Dis (*C2, C*1). It can reduce the transition time, search time, and store space in coding and decoding processes, where k < j. The third step was to choose a block within the first set whose distortion is the least and nearest to the *C1*. In this example, it is *C5*. In the fourth step, the *C*5 was used instead of the block *C*2. The distortion between *Ck* and the reference *C*1 was calculated to create the second set S2 of m blocks nearest to *C1*. In this example, block *C*11 replaces block C5 to create a new set of S3, and so on.

Using the dynamic rule with the TIE algorithm increases the transition speed, decreases search time, and reduces storage space. The steps used are as follows;

Initialize: divided an image into small, equal-sized blocks (i.e., *C1, C2, …Cj*). Determine the number of tries that are necessary. Calculate just the first set, S1, for each reference block, then go to the second set, S2, or third set, S3, and so on.
Step 1: Choose a block from the input image (*C1*) as the reference.
Step 2: Using Eq. 2, calculate the distortion for matching this block *C1* with *C2* (i.e., *Dis(C1, C2))*.
Step 3: Calculate the distance of matching each block *Cj* with *C1* to determine which of their distances is less than *2×Dis (C1, C2)* and put it in set (S1). In this case, the number of blocks in S1 (i.e., *k*) is less than the original number of blocks (j); therefore, the search space was reduced from j to *k*.
Step 4: Replace the *C2* with the block in the first set with the least distortion; in other words, the nearest block to the *C1* is *C5*.
Step 5: The *Dis(C1, C5) was* calculated.
Step 6: Calculate the distance of matching each block *Ck* in the first set (S1) with *C1* to determine which of their distances is less than 2×*Dis(C1, C5)* and put it in a new set (i.e., S2). In this case, the number of blocks in S2 (i.e., *m*) is less than S1 (m < k < j). The search space was reduced from *k* to m blocks.
Step 7: Take the block that has not been drawn in any final set and use it as a reference instead of C1. Then, repeat from step 1. See Fig. 1a and b.
Comparing the new reference block with the rest of the image blocks that are not included in any set means that each block in the image is either a reference block or is part of a set specific to a single reference. That is, a block cannot be in two places at the same time. This means that each block belonging to a specific reference has been compressed by sending only its location number relative to the other blocks in the reference.

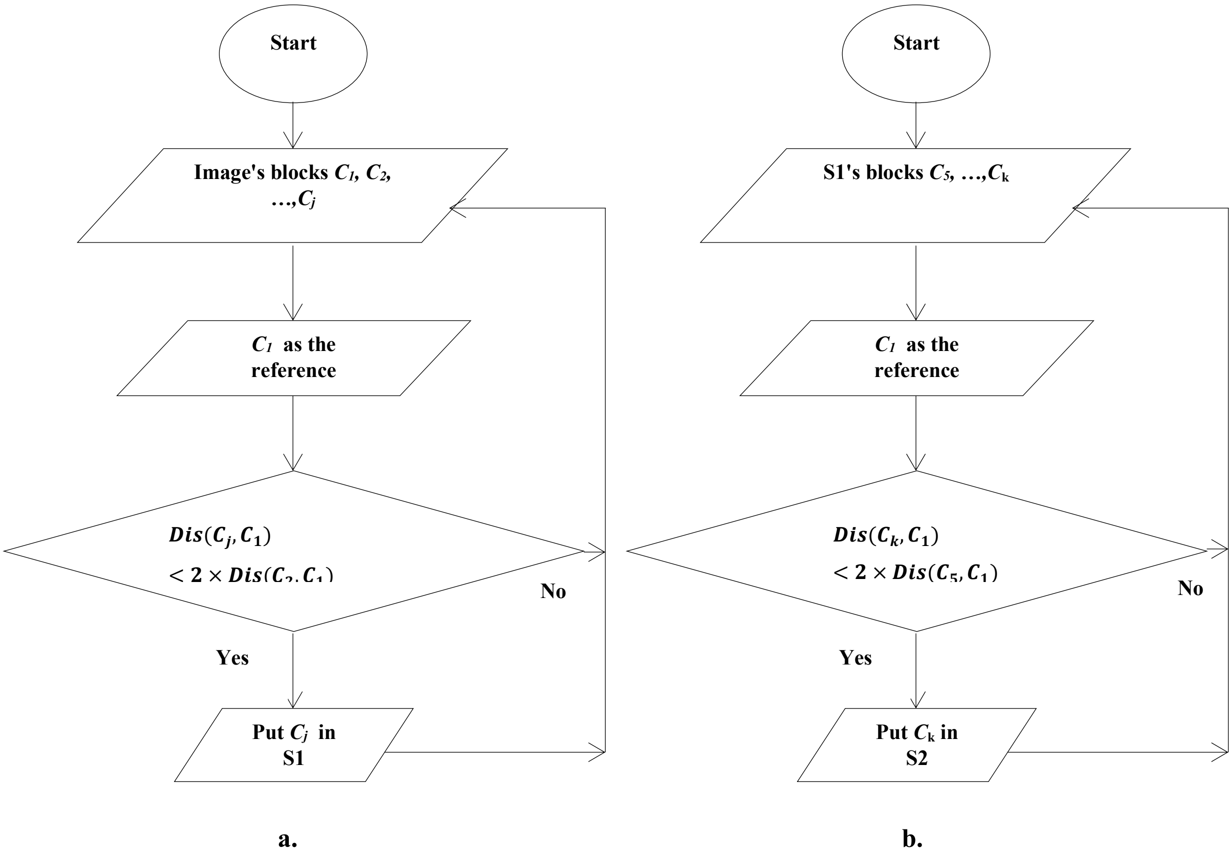

Figure 1: The flowcharts display the use of a. the TIE algorithm to find S1 and b. the D-TIE algorithm to find S2 when the reference is *C1*.

5. Results and Discussions

Table 1 compares the suggested approach using TIE for the first attempt (S1), D-TIE for multiple attempts from S2 to S4, and the conventional VQ method with a 256-block codebook. The data highlights the performance differences across the methodologies, indicating that the TIE and D-TIE approaches yield superior results in accuracy and efficiency. Furthermore, the analysis reveals that the VQ method, while effective, falls short when handling complex datasets compared to the innovative techniques proposed. It was noted that the suggested method, D-TIE, is faster in transmission and requires less storage space, as it generates a smaller number of blocks in the codebook and eliminates the need for search time to find the closest block. As a result, the computations were reduced, as the computations were less than S1 because the number of reference blocks is less than S2, S2 is less than S3, and so on. In other words, S1 is an ensemble of references (Set), where the references are image blocks instead of codewords in the VQ method. As seen in the example above, reference C is associated with the remaining blocks of the image that are close to it. S2 is also a set, but each reference represents fewer blocks closer to it. As a result, S2 will have more references than S1. S3 is also a set, but each reference is associated with a significantly smaller number of image blocks, which will only include those that are highly similar to that reference. That explains why S1 has fewer references than S2, S3, and S4. The table also displays the compression ratios of the TIE and D-TIE methods in comparison to the VQ method. It is noted that the higher the number of attempts, the higher the image quality at the expense of the compression ratio. However, the efficiency of the proposed method (D-TIE) is improved with a lower number of attempts, as it involves smaller reference blocks that represent the compressed image blocks, as shown in Fig. 2.

Table 1: The C.R., PSNR, and Computational Decreasing of TIE, D-TIE rules compared to the full search of the VQ method.

	Vector Quantization (VQ)	Elimination rule (TIE)	Dynamic and Elimination rules D-TIE		
		S_1	S_2	S_3	S_4
No. of references block	Codebook 256 (code words)	20	31	60	125
Compression Ratio (C.R)	8	28.211	21.331	16.00	11.631
MSE	32.146	58.317	44.201	38.254	34.110
PSNR	33.643	30.674	31.002	33.203	33.818
Computational Decreasing	—	73.431%	68.218%	%59.091	%51.031

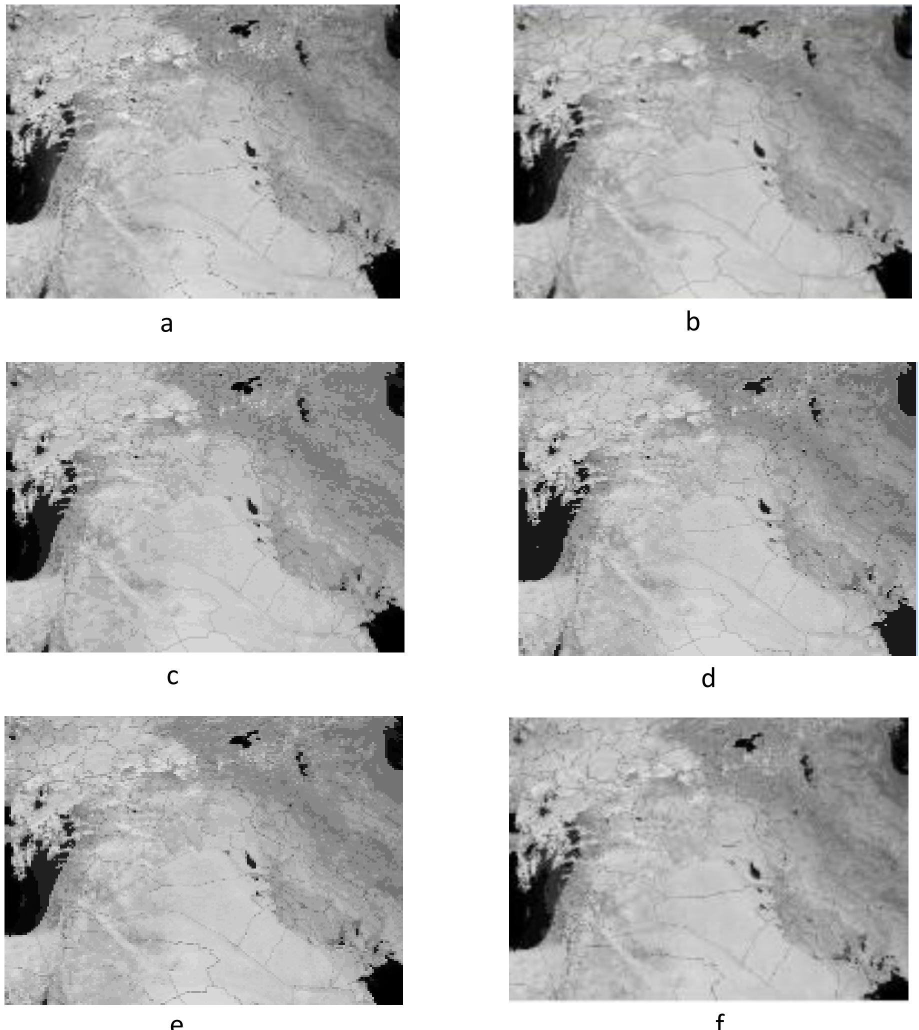

Figure 2: displays a) the original image (Iraq and Surrounding Regions), b) the outcome of the VQ method with a 256-codebook size, c) the result of using the TIE algorithm alone, and d, e, and f) the results of the proposed method D-TIE (S2, S3, and S4), respectively.

6. Conclusions

1- The study demonstrates that the dynamic rule, combined with the TIE algorithm, enhances the efficiency of the traditional TIE algorithm in image compression. Compared to vector quantization, the dynamic rule aims to reduce transition time and storage space by simplifying computation and accelerating search time in both coding and decoding steps. The results show that using the D-TIE leads to savings in computation, reaching 50% for the image of Iraq and the surrounding regions with good image quality, as shown in Table 1.

2- Using the VQ method with 256 codewords can achieve a higher picture quality (33.643) with a lower MSE value (32.146), but at the expense of a lower compression ratio of just 8. In the suggested method, using 20 references in group S1, the compression ratios are much more than 8, reaching 28.211. However, the image quality (30.674) decreases slightly as the execution speed increases. The speed of execution is attributed to the 20 references in group S1, which is significantly fewer than the 256 codewords. On the other hand, higher image quality (up to 33.818) with excellent compression ratios (better than the VQ method) can be achieved when the method is implemented for S4 = 125 due to the increased number of references in the set. The number of references in the set depends on the image, the proximity of the blocks to the reference, and the proximity of the blocks to each other. The closer the blocks are to each other in the image, the fewer the references, because many image blocks will belong to the same reference.

3- The numbers (20, 31, 60, and 125) represent the number of references in each group (S1, S2, S3, and S4), respectively. They were considered a codeword. The number of references in each group depends on the application of the proposed method, based on the number of blocks closest to each reference, as mentioned in the example above. Noticing that the number of references in S4 is 125 or more. This is due to the selection of only the blocks closest to the reference. The greater the number of references, the lower the compression ratio and the higher the image quality.

4- The running time of the proposed method varies from one computer to another, but this method is noticeably more efficient than the VQ method. Instead of sending and storing a codebook containing 256 codewords (256 blocks), this method only sends or stores a small number of references located in S1, S2, S3, and so on. Since the references are much smaller than 256 blocks, the transmission speed is faster, and the storage space required for the image is reduced.

References

[1] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2021.

[2] D. Ariatmanto and F. Ernawan, “An improved robust image watermarking by using different embedding strengths,” *Multimedia Tools and Applications,* vol. 79, no. 17, p. 12041–12067, 2020.

[3] D. O’Shaughnessy, “Review of methods for coding of speech signals,” *EURASIP Journal on Audio, Speech, and Music Processing,* vol. 1, no. 8, 2023.

[4] HP. Chan, R.K. Samala, L.M. Hadjiiski, C. Zhou, “Deep Learning in Medical Image Analysis,” *Advances in Experimental Medicine and Biology,* vol. 1213, 2020.

[5] P. Shan, “Image segmentation method based on K-mean algorithm,” *EURASIP Journal on Image and Video Processing,* vol. 1, pp. 1-9, 2018.

[6] S. M. Sawant and D. Batcheldor, “Charge-injection Device Imaging of Sirius with Contrast Ratios Greater than 1: 26 Million,” *Publications of the Astronomical Society of the Pacific,* vol. 134, no. 1033, p. 034503, 2022.

[7] R.R. Ismail, S. H. Halos, & B. Q. Al-Abudi, “Detection of the most frequent sources of dust storms in Iraq during 2020–2023 using space tools,” *Kuwait Journal of Science,* vol. 52, no. 1, p. 100328, 2025.

[8] R. Ablin, C. H. Sulochana, and G. Prabin, “An investigation in satellite images based on image enhancement techniques,” *European Journal of Remote Sensing,* vol. 53, no. sup2, pp. 86-94, 2020.

[9] A. I. Beena and B. ARTHI, “Contrast enhancement in gray-scale images using background approximation by blocks and morphological operations,” *Oriental Journal of computer science and Technology,* vol. 3, no. 1, pp. 69-73, 2010.

[10] M. A.Hameed, D.Mahdi, and Y. C. Bakheet, “Satellite image compression with enhancement low details regions depending on the background criteria,” in *AIP Conference Proceedings. 3408, 070002*, 2026.

[11] A. S. Abdulla, B. Q. Al-Abudi, & M. S. Mahdi , “Classification of Al-Hammar Marshes Satellite Images in Iraq using Artificial Neural Network based on Coding Representation,” *Indian Journal of Ecology,* vol. 45, no. 4, pp. 728-736, 2018.

[12] G. Lassalle, M. P. Ferreira, L. E. Cué La Rosa, R. D. M. Scafutto, and C. R. de Souza Filho, “Advances in multi-and hyperspectral remote sensing of mangrove species: A synthesis and study case on airborne and multisource spaceborne imagery,” *ISPRS Journal of Photogrammetry and Remote Sensing,* vol. 195, pp. 298-312, 2023.

[13] A. D. Boloorani, R. Papi, M. Soleimani, A. Al-Hemoud, F. Amiri, L. Karami, N. Samany, M.

Bakhtiari, and S. Mirzaei, "Visual interpretation of satellite imagery for hotspot dust sources identification," *Remote Sensing Applications: Society and Environment,* vol. 29, p. 100888, 2023.

[14] R. R. Ismail, B. Q. Al-Abudi and Z. F. Hussein, "Land cover change detection using satellite images based on modified spectral angle mapper method," *Plant Archives,* vol. 20, no. 1, pp. 2363-2371, 2020.

[15] H. M. Salih, "Adaptive speech compression based on AMBTC," *Periodicals of Engineering and Natural Sciences,* vol. 10, no. 2, pp. 199-206, 2022.

[16] B.Sujitha,V. S. Parvathy, E. L. Lydia, P. Rani, Z. Polkowski, and K. Shankar, "B.Sujitha,V.Optimal deep learning based image compression technique for data transmission on industrial Internet of things applications," *Optimal deep learning based image co Transactions on Emerging Telecommunications Technologies,* vol. 32, no. 7, p. 3976, 2021.

[17] Y. Linde, A. Buzo, and R. M. Gray, "An algorithm for vector quantizer design," *IEEE Transactions on Communications,* vol. 28, no. 1, pp. 84-95, 1980.

[18] A.A. Alhadi, "Compression of Medical Images Based on 2D-Discrete Cosine Transform and Vector Quantization Algorithms," *Bani Waleed University Journal of Humanities and Applied Sciences,* vol. 8, no. 3, pp. 168-179, 2023.

[19] M. E. Celebi, H. A. Kingravi, and P. A. Vela, "A comparative study of efficient initialization methods for the k-means clustering algorithm," *Expert Systems with Applications,* vol. 40, no. 1, p. 200–210, Jan. 2013.

[20] I. A. Huijben, I. A., M. Douze, M. Muckley, R. J. Van Sloun, and J. Verbeek, "Residual Quantization with Implicit Neural Codebooks," arXiv preprint arXiv:2401.14732, 2024.

[21] C. Gong, Y. Chen, Y. Lu, T. Li, C. Hao and D. Chen, "MVQ: Towards Efficient DNN Compression and Acceleration with Masked Vector Quantization," *arXiv preprint arXiv:2412.10261,* 2024.

[22] Z. Cheng, H. Sun, M. Takeuchi, and J. Katto, "Deep Convolutional AutoEncoder-based Lossy Image Compression," *2018 Picture Coding Symposium (PCS),* p. 253–257, 2018.

[23] M. Bilal, Z. Ullah, and I.U. Islam, "Fast codebook generation using pattern based masking algorithm for image compression," *IEEE Acces,* vol. 9, pp. 98904-98915, 2021.

[24] J. Shin, Y. Kang, and Y.-S. Jeon, "Vector Quantization for Deep-Learning-Based CSI Feedback in Massive MIMO Systems," *arXiv preprint arXiv:2403.07355,* 2024.

[25] M. H. Vali and T. Bäckström, "Stochastic Optimization of Vector Quantization Methods in Application to Speech and Image Processing," in *in IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP 2023)*, 2023.

[26] T. Vallaeys, M. Muckley, J. Verbeek, and M. Douze, "Qinco2: Vector Compression and Search with Improved Implicit Neural Codebooks," *arXiv preprint arXiv,* vol. 2501, p. 03078, 2025.

[27] T. Li, V. Sivaraman, P. Karimi, L. Fan, M. Alizadeh, and D. Katabi, "Reparo: Loss-resilient generative codec for video conferencing," 2023.

[28] Y. C. Wu,I. D. Gebru, D. Markovic, and A. Richard, "Audiodec: An open-source streaming high-fidelity neural audio codec," in *In ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2023.

[29] T. Azfar, J. Li, H. Yu, R. L. Cheu,Y. Lv, and R. Ke, "Deep learning-based computer vision methods for complex traffic environments perception," *Data Science for Transportation,* vol. 6, no. 1, 2024.

[30] G. Corominas, M. J. Blesa, and C. Blum, "Accelerating the k-means++ algorithm by using geometric information," *IEEE Access,* 2025.

[31] C. Elkan, "Using the triangle inequality to accelerate k-means," in *In Proceedings of the 20th international conference on Machine Learning (ICML-03)*, 2003.