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Original Article

Analytical and Empirical Survival Study on Natural Image Compression and Classification using Machine Learning Techniques

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***Abstract** - Image processing is used to analyse and manipulate digitised images to increase image quality. Image pre-processing minimises noise, enhances contrast, smoothing and sharpening, and performs advanced operations. Feature extraction is the method of describing the set of features or image characteristics for analysis and classification. A feature is a piece of information about image content with properties. The feature extraction process extracts the essential features from the input image. Image classification is a process based on the segregation of object similarity values. Image compression is a method where the original image gets encoded with a small number of bits. Image compression is used for digital images to minimise storage and transmission costs. Many researchers carried out their research on natural image feature extraction, classification and compression methods. But, the peak signal-to-noise ratio was not improved, and time consumption was not reduced. The different image filtering, compression and classification methods with natural images are reviewed in analytical and empirical terms to address the existing problems.*

***Keywords** - Contrast enhancement, Feature extraction, Filtering, Image classification, Image compression, Image smoothing, Image processing.*

1. Introduction

Digital images are essential in daily life for different applications like medical imaging, video surveillance, criminal investigations, remote sensing etc. The image collected from the digital cameras reduced the contrast and brightness because of imaging subsystem and illumination conditions while capturing an image. Image classification is important in remote sensing images for applications like environmental change, agriculture, land use/land planning, urban planning, surveillance, geographic mapping, disaster control and object detection. The remote sensing image is obtained from satellites, airplanes, and aerial vehicles. Features included the specific structures in the image like points, edges or objects. Classification is the process of categorising natural images into diverse classes based on the objects in the images. Image compression is a lossless image compression or lossy image compression. Lossless image compression is used for medical images, technical illustrations, satellite images and images for archival reasons. Lossy compression is used where the small loss in image retrieval is handled. Image compression is used to preserve essential characteristics of the original image in reconstruction.

2. Literature Review

A new Retinex-based low-light image enhancement method was designed in [1] with Retinex image decomposition in a semi-decoupled manner. The illumination layer was determined with input image gaussian total variation. But, the peak signal-to-noise ratio was not increased by the designed method. An automatic image enhancement method was introduced in [2] with quality results for images collected under exposure conditions. Images were categorised with a convolutional neural network (CNN) to determine a class with different weight coefficients for processing. However, the pre-processing time was not reduced by the designed method. The automatic image enhancement method is not extended to handle the dark regions and eliminate the noise.

A coloured image correction method was designed in [3] based on nonlinear functional transformation with an illumination-reflection model and multi-scale theory to increase the adaptability of image enhancement with minimal illumination. But, the computational time was not reduced by the coloured image correction method. A regularised illumination optimisation and deep noise suppression method were designed in [4] to improve the low-light images. A hybrid regularised variational model joined L0-norm gradient sparsity prior with structure-aware regularisation to refine the coarse illumination map determined through Max-RGB. But, the peak signal-to-noise ratio was not increased by the designed method.

A multi-feature fusion VR panoramic image shadow elimination algorithm was designed in [5] to use the HSV colour features, and Local Binary Pattern (LBP)/ Local Five Similarity Pattern (LSFP) texture features to achieve shadow detection results. But, the space complexity was not reduced by the designed algorithm. A robust two-fold approach was introduced in [6] for identifying the trees in a real-world natural setting. A single-GPU implementation was performed for feature recognition with annotated data and achieved high accuracy and bark correspondingly. But, the feature extraction time was not minimised by a robust two-fold approach.

The Genetic Programming (GP) approach was introduced in [7] with program representation, function and terminal. A new mutation operator was introduced depending on the population's fitness for different sizes of GP programs. However, the feature extraction accuracy was not improved by the GP approach. A low-rank matrix regression model was designed in [8] for feature extraction and feature selection with structure information. An optimisation algorithm was designed depending on the alternating direction with multiplier and objective function. But, the feature extraction time was not reduced by the low-rank matrix regression model.

A convolutional graph network (GCN) was designed in [9] for drainage pattern recognition. A dual graph of drainage was constructed with the channel connection and hierarchical structure. The features were extracted from global unity, connectivity and local equilibrium. However, the complexity level was not reduced by GCN. A new algorithm was presented in [10] with scene images to extract the Region of Interest (ROI). Bangla words were divided from the sentence by analysing connected components (CC) and bounding box techniques. However, the computational cost was not reduced by the CC technique.

An automated approach was designed in [11] to identify the concrete crack pattern from images. The crack pattern classification was carried out with isolated and map patterns. But, the computational complexity was not reduced by an automated approach. A convolutional neural network-based pipeline was introduced in [12] to achieve high-level visual features for enhanced text detection and recognition efficiency. An improved ReLU layer block was used with a receptive field to find the text components. But, the pattern recognition accuracy rate was not minimised by the convolutional neural network-based pipeline.

A new multimodal compression scheme was designed in [13] for compressing images and signals through a single codec. The designed scheme was to insert a wavelet-decomposed signal into the decomposed image to consider the mixture data for compression with Set Partitioning In Hierarchical Trees (SPIHT) encoder. But, the space complexity was not minimised by the multimodal compression scheme. An image compression technique was introduced in [14] with discrete wavelet transformation (DWT) to protect the textural features of the image. The image was categorised into the featured region and non-featured region. The regions were captured for allocating the textural descriptor through fuzzy clustering methods. But, the compression ratio was not improved by the designed technique.

A new image compression method was introduced in [15] for accurate 3D reconstruction from 2D images. The designed method depended on discrete cosine transform (DCT) with a high-frequency minimisation encoding algorithm at the compression stage and a binary search algorithm at the decompression stage. But, the compression time was not minimised by the designed method.

3. Natural Image Classification and Compression for Quality Enhancement

Digital image processing system is used in many areas like industrial production, video surveillance, intelligent transportation, remote sensing, and monitoring. The images were collected through image acquisition systems because of different defects that arise from uncontrollable factors during the image acquisition process under unfavourable conditions like indoor lighting, nighttime lighting and cloudy weather. The reflection of the target surface was weak, and colour was distorted through considerable noise, leading to degradation in image quality to prevent the visual systems. Image enhancement technique provided a possible solution to satisfy the better visual experience and improve the reliability and robustness of outdoor vision systems. Image compression is the technique used to minimise the unnecessary information of the image to store and transmit cost-effectively.

3.1. Low-Light Image Enhancement with Semi-Decoupled Decomposition

Images were considered under imperfect light conditions with low contrast and strong noise. The visual effects were undesirable, making the images less appealing. It was valuable to enhance the images in contrast correction, recovering details and noise suppression. The task was considered the low-light enhancement, contrast enhancement or exposure correction to enhance the visual image quality. Low-light image enhancement was essential for the high-quality visual application.

An image quality enhancement increases image visibility with visual naturalness. The retinex-based technique was considered a representative method. Different artifacts were employed to attain enhanced results because of image decomposition or strong imaging noise. A priori was modelled through regularisation terms for addressing the optimisation process. A new retinex-based low-light image enhancement method was introduced with Retinex image decomposition in an efficient semi-decoupled way.

An illumination layer 'I' was estimated with the input image 'S' depending on the Gaussian Total Variation model. The reflectance layer 'R' was estimated by 'S' and the intermediate 'I'. An imaging noise was suppressed during 'R' estimation. An edge-preserving image filter was introduced depending on Gaussian Total Variation to perform better piecewise smoothing and texture removal. A semi-decoupled decomposition model was employed for estimating 'I' and 'R' to satisfy high decomposition quality and fast convergence.

3.2. Efficient Image Enhancement Model for Correcting Uneven Illumination Images

Images collected under different light conditions have deficient contrast, low brightness, latent colour and high noise. Many techniques were introduced for enhancing specific images and failed to restore the artifact-free results for different images. An automatic image enhancement method was introduced to produce high-quality results with images captured under uneven exposure conditions.

A deep convolutional neural network (CNN) was introduced to categorise the images into different classes. The input image and degree were chosen depending on the trained model. The key objective of the classification task was to classify the images for enhancement frameworks with a specific degree. The bright channel prior and edge-preserving filter computed an initial transmission map.

Images were classified through a convolutional neural network (CNN) to determine their class. Different weight coefficient values were attained for further processing. Images were converted into photonegative form to attain an initial transmission map through a bright channel. L1-norm regularisation was employed to process the scene transmission. An environmental light was computed based on an efficient filter.

An image degradation model was employed to attain enhanced results. Image post-processing comprised denoising and details enhancement. The denoised model was applied when images were gathered in extreme low-light conditions. A smooth layer was obtained through L1-norm regularisation to improve the details in partially over- and under-exposed images. The denoised model was adopted for images collected in a complex light environment. The designed model increased illumination and degraded images automatically.

3.3. Adaptive Image Enhancement Method for Correcting Low-Illumination Images

A coloured image correction method depending on nonlinear functional transformation was introduced with the illumination-reflection model and multi-scale theory to improve the adaptability of image enhancement with low illumination. An original RGB image was changed to HSV colour space. V component was employed to extract the illumination component of the scene through a multi-scale Gaussian function.

A correction function was built depending on Weber-Fechner law. Two images were attained through the adaptive adjustment to the image enhancement function parameters depending on the distribution profiles of illumination components. An image fusion strategy was determined to extract the details from two images. The designed method increased an image's overall brightness and contrasted while minimising the uneven illumination impacts. The enhanced images appeared as clear, bright, and natural. The illumination component values were extracted through multi-scale Gaussian functions to describe the illumination variation without detailed information.

After extracting the illumination component of the scene, the illumination enhancement function was constructed consistent with the distribution profile of the illumination component. An adaptive brightness correction method depending on Weber-Fechner law was used to adjust enhancement function parameters consistent with the image illumination components' distribution profile. The designed method was employed to improve the overall image quality with uneven illumination. Using Weber-Fechner law, the subjective brightness perceived by the human eye was created when light rays reflected from objects hit the retina of the human eye and stimulate the optic nerves.

3.4. An Improved Multimodal Signal-image Compression Scheme with Application to Natural Images and Biomedical Data

A new multimodal compression scheme was introduced for compressing the image and signal through a single codec. The designed scheme was used to insert a wavelet-decomposed signal into the decomposed image. The designed scheme considered the mixture data of an image for compression with Set Partitioning In Hierarchical Trees (SPIHT) encoder. The insertion stage was performed with wavelet sub-bands with a spiral insertion function. The evaluation process was assessed on natural and medical images consistent with objective and subjective criteria. Multimodal compression schemes were provided for a fair evaluation. The designed scheme was employed to attain important gains regarding the Percentage of Root Mean Square Difference (PRD) and Peak Signal to Noise Ratio (PSNR) for reconstructed signal and image. A new wavelet-based multimodal compression approach was introduced to compress images and signals by the SPIHT coder. Multimedia Tools Application invested in energy compaction property of DWT for signal and image. The wavelet coefficients were clustered and quantised to zero values. When handling the low computational complexity, the designed approach provided the image reconstruction and inserted signal without perceptual artifacts causing noticeable distortions for biomedical data.

3.5. Image Compression and Reconstruction by Examplar-based Inpainting using Wavelet Transform on Textural Regions

A new image compression technique was introduced with discrete wavelet transformation (DWT) and examplar-based image inpainting. The designed technique was used to protect the image's textural features. The image was categorised into the featured region and non-featured region. The regions were captured texturally for allocating the textural descriptor through fuzzy clustering methods. The descriptors of textural region integrated the coexistence matrices with features attained through coherence analysis. A discrete wavelet transform was applied to the region where the input image gets partitioned. The number of wavelet coefficients was chosen based on the nature of textural clustering. The compression ratios were attained for separate regions. Every reconstructed region was combined linearly together to modernise the original image. The designed technique attained larger coding performance and plausibly reconstructed the compressed image similar to the original image.

3.6. A Novel High-Frequency Encoding Algorithm for Image Compression

A new image compression method was introduced, describing quality through 3D reconstruction from 2D images. The designed method depended on discrete cosine transform (DCT) with a high-frequency minimisation encoding algorithm at the compression stage and a concurrent binary search algorithm at the decompression stage. The compression method comprised five processes. The first step of the designed method partitioned the image into blocks and related the DCT to every block. The second step of the designed method employed high-frequency minimisation to the AC-coefficient by reducing every block by 2/3 minimised array. The third step of the designed method constructed the lookup table of probability data to allow the recovery of original high frequencies at the decompression stage. The design method's fourth step was to relate the delta or differential operator to the DC components. The fifth step of the designed method was to perform the arithmetic encoding to outputs. The lookup table and the concurrent binary search algorithm were employed at the decompression stage to reconstruct all high-frequency AC coefficients. The DC components were decoded by reversing the arithmetic coding. An inverse DCT recovered the original image. The designed method compressed and decompressed the 2D images with structured light patterns for 3D reconstruction.

4. Performance Analysis of Natural Image Classification Methods

Experimental evaluation of existing natural image classification techniques is implemented using Matlab software. The experiment of existing natural image classification techniques is conducted using Satellite Image Classification taken from the Kaggle. The URL of the mentioned dataset is given as https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification. The dataset has 4 different classes mixed from Sensors and google map snapshots. Result analyses are carried out with existing methods with parameters are,

- Classification accuracy
- Classification time
- Error rate
- Compression ratio

4.1. Analysis of Classification Accuracy

Classification accuracy is defined as the ratio of the number of natural images that are correctly classified to the total number of natural images. It is formulated as,

$$Class_{Acc} = \frac{Number\ of\ natural\ images\ that\ are\ correctly\ classified}{Total\ number\ of\ natural\ images} * 100 \quad (1)$$

From (1), '$Class_{Acc}$' denotes the classification accuracy. It is represented in terms of percentage (%).

Table 1. Tabulation of Classification Accuracy

Number of Natural Images (Number)	**Classification Accuracy (%)**		
	Novel retinex-based low-light image enhancement method	**Deep CNN**	**The coloured image correction method**
100	85	78	71
200	88	80	74
300	90	83	76
400	92	86	79
500	91	84	77
600	88	82	75
700	86	80	73
800	89	83	76
900	91	85	78
1000	93	87	80

Table 1 explains the classification accuracy for satellite images ranging from 100 to 1000. Classification accuracy comparison takes place on the existing Novel retinex-based low-light image enhancement method, Deep Convolutional Neural Network (CNN) and Colored image correction method. Let us consider the number of satellite images as 800; the classification accuracy of the novel retinex-based low-light image enhancement method is 89%. The classification accuracy of Deep CNN and the Colored image correction method is 83% and 76%. The graphical representation of classification accuracy is described in figure 1.

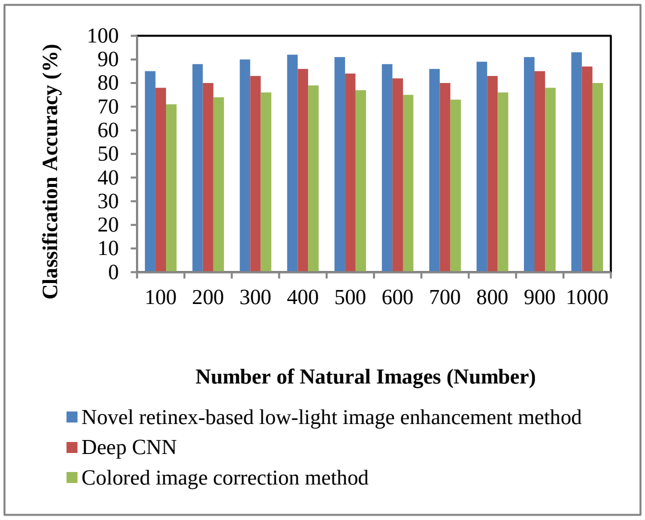

Fig. 1 Measurement of Classification Accuracy

Figure 1 describes the classification accuracy for a different number of satellite images. The blue colour pyramid symbolises the classification accuracy of the Novel retinex-based low-light image enhancement method. The red colour cylinder and green colour pyramid denote the corresponding classification accuracy of the Deep Convolutional Neural Network (CNN) and Colored image correction method. The classification accuracy using the Novel retinex-based low-light image enhancement method is higher when compared to the Deep CNN and Colored image correction method. It is because of applying edge-preserving image filters depending on Gaussian Total Variation to attain better classification performance by using piecewise smoothing and texture removal. This, in turn, helps to increase classification accuracy. As a result, the classification accuracy of the Novel retinex-based low-light image enhancement method is increased by 8% compared to the Deep CNN and 18% compared to the coloured image correction method.

4.2. Analysis of Error Rate

The error rate is defined as the ratio of the number of natural images that are incorrectly classified to the total number of natural images. It is given as,

$$Error_{Rate} = \frac{Number\ of\ natural\ images\ that\ are\ incorrectly\ classified}{Total\ number\ of\ natural\ images} * 100 \quad (2)$$

From (2), '$Error_{Rate}$' symbolises the error rate. It is represented in terms of percentage (%).

Table 2. Tabulation of Error Rate

Number of Natural Images (Number)	Error Rate (%)		
	Novel retinex-based low-light image enhancement method	Deep CNN	The coloured image correction method
100	35	27	40
200	33	23	38
300	37	26	41
400	39	28	43
500	38	27	42
600	40	30	44
700	44	33	46
800	46	35	48
900	49	38	50
1000	51	40	53

Table 2 explains the error rate for satellite images ranging from 100 to 1000. Error rate comparison takes place on the existing Novel retinex-based low-light image enhancement method, Deep Convolutional Neural Network (CNN) and Colored image correction method. Let us consider the number of satellite images as 500; the error rate of the novel retinex-based low-light image enhancement method is 38%. The error rate of Deep CNN and Colored image correction methods are 27% and 42%. The graphical representation of the error rate is illustrated in figure 2.

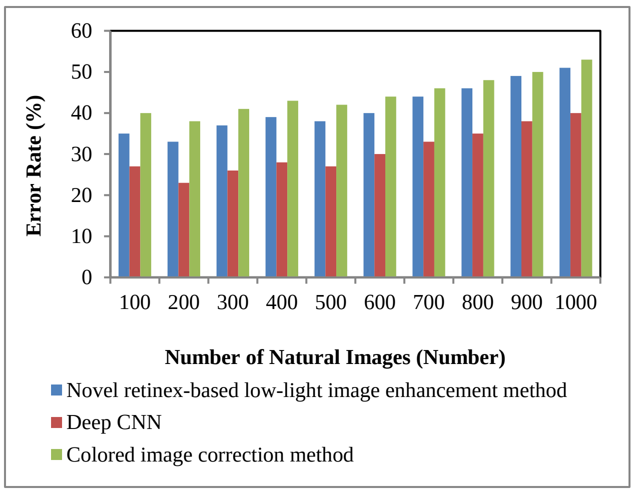

Fig. 2 Measurement of Error Rate

Figure 2 describes the error rate for the different numbers of satellite images. The blue colour pyramid symbolises the error rate of the Novel retinex-based low-light image enhancement method. The red colour cylinder and green colour pyramid denote the error rate of the Deep Convolutional Neural Network (CNN) and the Coloured image correction method correspondingly. It is observed that the error rate using Deep CNN is lesser when compared to the Novel retinex-based low-light image enhancement method and the Coloured image correction method. This is because of applying L1-norm regularisation to process the scene transmission. An environmental light was determined depending on an efficient filter. This, in turn, helps to reduce the error rate. As a result, the error rate of Deep CNN is reduced by 26% compared to the Novel retinex-based low-light image enhancement method and 31% compared to the coloured image correction method.

4.3. Analysis of Classification Time

Classification time is defined as the product of the number of natural images and time consumed to perform the classification of one natural image. It is calculated as,

$$Class_{Time} = N * \text{time consumed to perform natural image classification} \quad (3)$$

From (3), '$Class_{Time}$' symbolises the classification time. It is represented in terms of milliseconds (ms).

Table 3. Tabulation of Classification Time

Number of Natural Images (Number)	Classification Time (ms)		
	Novel retinex-based low-light image enhancement method	Deep CNN	The coloured image correction method
100	35	22	18
200	38	24	20
300	40	27	22
400	42	29	25
500	45	31	28
600	48	34	30
700	50	36	32
800	52	38	34
900	55	40	37
1000	59	43	39

Table 3 describes the classification time for satellite images ranging from 100 to 1000. Classification time comparison takes place on the existing Novel retinex-based low-light image enhancement method, Deep Convolutional Neural Network (CNN) and Coloured image correction method. Let us consider the number of satellite images as 300; the classification time of the novel retinex-based low-light image enhancement method is 40ms. The classification time of Deep CNN and the Colored image correction method is 27ms and 22ms. The graphical representation of classification time is described in figure 3.

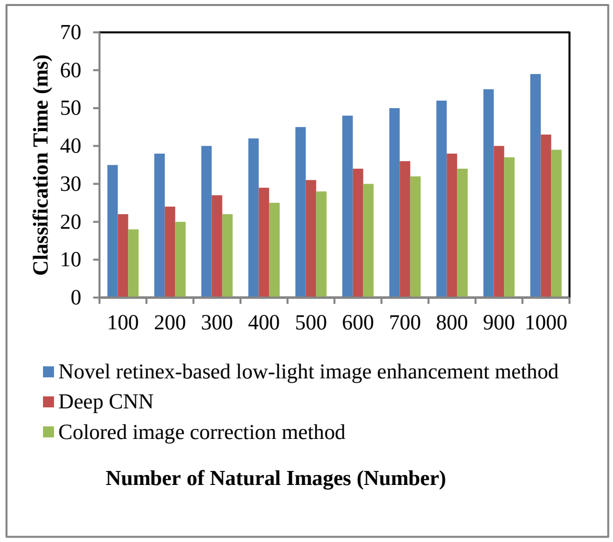

Fig. 3 Measurement of Classification Time

Figure 3 illustrates the classification time for the different numbers of satellite images. The blue colour pyramid symbolises the classification time of the Novel retinex-based low-light image enhancement method. The red colour cylinder and green colour pyramid denote the corresponding classification time of the Deep Convolutional Neural Network (CNN) and the Coloured image correction method.

The classification time using the Coloured image correction method is lesser when compared to the Novel retinex-based low-light image enhancement method and Deep CNN. It is because of using the image fusion strategy to extract the information from images and to increase the brightness and contrast of an image while reducing the uneven illumination impacts. This, in turn, helps to reduce the classification time. As a result, the classification time of the Coloured image correction method is reduced by 39% when compared to the Novel retinex-based low-light image enhancement method and 13% when compared to the Deep CNN.

4.4. Analysis of Compression Ratio

The compression Ratio is the ratio of the original image to the compressed data. The compression ratio is calculated as,

$$Compression\ ratio = \frac{Uncompressed\ image\ size}{Compressed\ image\ size} \quad (4)$$

From (4), a compression ratio of different image sizes is achieved. The technique is more efficient when the compression ratio is higher.

Table 4. Tabulation of Compression Ratio

Natural Image Name	Image Size (KB)	Compression Ratio		
		Multimodal compression scheme	Image compression technique	The new image compression method
Image 1	4.24	19	13	9
Image 2	10.06	22	15	10
Image 3	4.71	18	16	12
Image 4	2.94	14	11	8
Image 5	3	16	14	10
Image 6	3.01	13	9	5
Image 7	2.92	11	8	4
Image 8	2.97	14	9	7
Image 9	2.93	17	14	11
Image 10	3	20	17	14

Table 4 describes the compression ratio for different satellite image sizes. Compression ratio comparison takes place on the existing multimodal compression scheme, image compression technique and new image compression method. Let us consider that natural image 5 with the size of 3KB, the compression ratio of the multimodal compression scheme is 16. The compression ratio of the image compression technique and the new image compression method are 14 and 10. The graphical representation of the compression ratio is illustrated in figure 4.

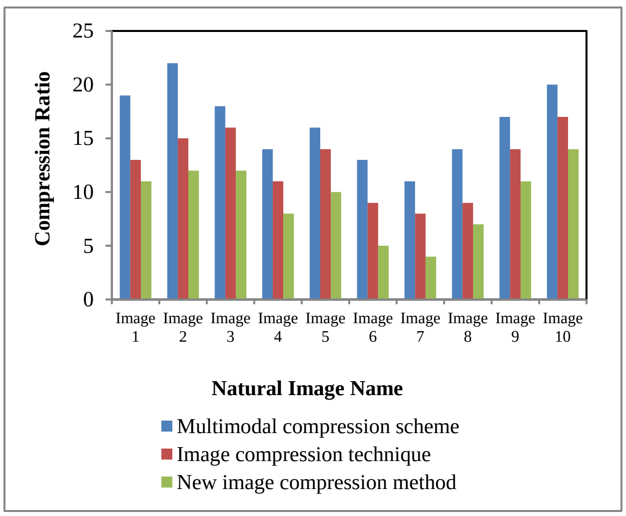

Fig. 4 Measurement of Compression Ratio

The above figure 4 shows the compression ratio for different satellite image sizes. The blue colour pyramid symbolises the compression ratio of the multimodal compression scheme. The red colour cylinder and green colour pyramid denote the compression ratio of the image compression technique and the new image compression method, respectively. The compression ratio using a multimodal compression scheme is higher when compared to the image compression technique and the new image compression method. It is because of using a wavelet-based multimodal compression approach to compress the image and signal by SPIHT coder. Multimedia Tools Application invested in energy compaction property of DWT for signal and image. This, in turn, helps to improve the compression ratio. As a result, the compression ratio of the multimodal compression scheme is increased by 32% when compared to the image compression technique and 87% when compared to the new image compression method.

5. Discussion and Limitations of Satellite Image Compression and Classification Methods

A new Retinex-based low-light image enhancement method performed the Retinex image decomposition semi-decoupled way. The illumination layer was determined with the input image based on the gaussian total variation model. The imaging noise was suppressed during the estimation of the reflectance layer. But, the designed method failed to enhance dark regions without preference. The solution did not leverage social information to enhance the strengths of indifferent image regions.

A deep convolutional neural network (CNN) attained high-quality results with images gathered under uneven exposure conditions with one-sided illumination and nighttime images. L1-norm regularisation was adapted to process scene transmission. But, the designed method failed to adopt photographic semantic analysis and image synthesis. The designed method is not extended properly to handle dark regions and eliminate noise.

A coloured image correction method was introduced based on nonlinear functional transformation to increase adaptability with low illumination. An image fusion strategy extracted the details from the two images. The designed algorithm increased image brightness and contrast with uneven illumination. But, the designed method failed to enhance video images, and additional effort was required to improve its real-time performance. The computational time was not reduced by the coloured image correction method.

A new multimodal compression scheme was introduced for compressing the image and signal through a single codec. The designed scheme was employed to insert the wavelet-decomposed signal into the decomposed image to consider the mixture data for image compression. But, the space complexity was reduced by the new multimodal compression scheme.

A novel image compression technique was introduced with discrete wavelet transformation (DWT) and examplar-based image inpainting. The designed technique was employed to preserve the image's textural features. The image was categorised into the featured region and non-featured region. The regions were collected for allocating the textural descriptor through fuzzy clustering methods. However, the compression ratio was not reduced by the image compression technique.

An image compression method was introduced through accurate 3D reconstruction from 2D images depending on discrete cosine transform (DCT) with a high-frequency minimisation encoding algorithm at the compression stage and a binary search algorithm at the decompression stage. However, the compression time was not minimised by the image compression method.

5.1. Future Direction

The future direction of the satellite image compression and classification methods is to improve the accuracy and reduce time consumption using machine learning and deep learning methods.

6. Conclusion

A comparative study of different satellite image compression and classification methods is carried out. From the study, the new Retinex-based low-light image enhancement method failed to enhance the dark regions without preference. In addition, the Deep CNN failed to adopt photographic semantic analysis and image synthesis. The image compression technique did not reduce the compression ratio. The new multimodal compression scheme reduced the space complexity. The computational time was not reduced by the coloured image correction method. The wide experiment on conventional image compression and classification techniques estimates the result of different satellite image compression and classification methods and discusses its problems. From the result analysis, the research can be carried out using machine learning and ensemble learning techniques for efficient satellite image compression and classification with higher classification accuracy and less time consumption.

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