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Survey on Feature Extraction of Discrete Cosine Transform(DCT)Coefficient that we use to Fuse two Images

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مراجعه لطرق استخراج معاملات DCTالتي سوف نستخدمها في دمج صورتين

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ABSTRACT

Background: Image fusion based on the Discrete Cosine Transform (DCT) is a method employed to fuse multiple images into a single composite image. This technique enhances visual quality and extracts valuable information from the input images.

Materials and Methods :The Discrete Cosine Transform (DCT) is a commonly utilized transformation technique in signal processing and image compression. It offers a means to represent an image about its frequency components.

Results: The outcome of image fusion is a composite image that fusion the input images while maintaining crucial details and extracting valuable information. Through the application of the average fusion rule to the DCT coefficients of the source images, the fused image is generated. This outcome generally enhances visual quality.

Conclusion: The fused image combined all the important information in both images. The quality of the resulting image is superior to the quality of the input images. This one image has all the relevant information and is more accurate and informative than any image from a single source.

Key words: Image fusion, Feature extraction, DCT, Fused image, Performance evaluation

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1. INTRODUCTION

Image fusion using the Discrete Cosine Transform (DCT) is a well-established technique in computer vision and image processing. It involves combining multiple images by utilizing the frequency domain representation provided by the DCT, resulting in a composite image that contains enhanced information[1]. The DCT is a widely used transform for converting images from the spatial domain to the frequency domain, enabling effective analysis and manipulation of image data. The problem statement loss of spatial details is a significant concern in image fusion based on DCT. The use of DCT-based fusion methods often leads to a reduction in fine spatial information since the focus of the transform is on frequency representation rather than preserving precise spatial details. As a result, the quality and accuracy of the fused image can be adversely affected. Another issue pertains to the inadequate representation of relevant features. DCT may not sufficiently capture and represent all the essential features necessary for fusion, such as edges or textures. This limitation can result in suboptimal fusion outcomes and an insufficient preservation of accurate features in the fused image[2]. Image fusion has diverse applications in remote sensing, medical imaging, surveillance, and multimedia, aiming to improve the quality, clarity, and interpretability of the resulting composite image[3]. By integrating complementary information from input images, image fusion enables a more comprehensive representation of the scene or object of interest[4]. The fusion process relies on the DCT and involves several essential steps. First, the input images undergo preprocessing to eliminate noise, correct distortions, and enhance overall quality. Then, the DCT transformation is applied to each input image, converting them to the frequency domain. This transformation represents the images as a collection of DCT coefficients, highlighting the various frequency components present. To achieve fusion, a fusion rule is applied to the DCT coefficients of the input images, determining how they are combined to generate fused coefficients. Different fusion strategies can be employed, such as weighted averaging, maximum coefficient selection, or other algorithms tailored to specific requirements. Finally, the fused coefficients are inverse transformed using the inverse DCT, resulting in the final fused image in the spatial domain[5].

Image fusion encompasses various approaches, including simple averaging, selection of maximum coefficients, discrete wavelet, discrete cosine, complex two-tree wavelet, high-pass filtering, color density, principal component analysis, unbranched contour, and even frequency[6]. The objective of image fusion is to gather all necessary data from any source image, as some images may lack complete information. Multi-focus image fusion is utilized to extract important background information from input images[7]. The advantages of image fusion include reducing uncertainty, improving geographical and temporal coverage, increasing reliability, and enhancing system performance robustness. However, choosing the optimal fusion method for integrating multiple source images remains a fundamental challenge. An ideal image fusion technique should exhibit three key characteristics: high computing efficiency, preservation of high spatial resolution, and reduction of color distortion[8].

There are four image fusion levels: Pixel-level fusion, Fusion at the block level, Feature-level fusion, and Decision-level fusion. Pixel-level fusion to improve implementation accuracy, This type of image fusion is built using data that is fixed at a set of pixels in the input signals. Fusion at the block level is based on the data's neighborhood points. Feature level fusion This activates the distinct appearance of the data, such as pixel intensities, sizes, and edges. The supplied photos' characteristics are mixed. Decision level fusion to create a final decision image, the output from many algorithms is combined[2].

There are three models of image fusion: multi-view fusion, multi-modal fusion, and multi-focus fusion. The multi-view fusion approach combines 3D equivalent value data from different views into a single image. Multimedia image merging involves combining models to create a single image, meaning it uses several different scenes rather than just one scene. Multi-focus object merging technique combines details and essential information from two or more images into one focused image. This means using a series of a specific scene with some minor changes[1].

There are two image fusion systems: Single Sensor Fusion System(SSFS) In situations where only one sensor is available, photographs are taken and processed using a single device. The goal is to capture the specific scene, and the resulting image sequence is then merged into a single composite image. However, relying on a single sensor poses a significant disadvantage since issues can arise due to the limitations of the sensor's performance[9]. Single Sensor Fusion System It is the use of a series of images of a specific scene with few changes in the scene and A Multi-Sensor Fusion System (MSFS) utilizes multiple sensors to track objects and capture images. The system captures a sequence of photos using different sensors and combines them to create a single image that ensures all elements are in clear focus. A Multi-Sensor Fusion System It is the use of a series of images for several scenes[9][10].

The presented work focuses on image fusion based on discrete cosine transform for combining multiple images and discovering distinctive features, addressing the challenges associated with image fusion. The main objective of the project is to fuse several images taken under different conditions of the same scene into a single image, emphasizing the importance of using effective feature representation techniques and feature extraction strategies.

2. DISCRETE COSINE TRANSFORM(DCT)

The discrete cosine transform (DCT) is a suitable method in image processing that partitions the image into components of varying importance, each corresponding to a specific frequency range (low and high frequencies). The higher coefficients predominantly capture information from the low-frequency region, while the high-frequency coefficients represent the edges of the image. By employing the DCT, the image can be divided into segments or spectral sub-bands that possess different levels of significance in terms of visual quality. The DCT facilitates the transformation of a signal or image from the spatial domain to the frequency domain, enabling a more effective analysis of its frequency components[1].

The process of DCT image fusion involves the following steps as shown in Fiq.1:

1-The input images are divided into blocks of size 8×8.

2-For each block, the following steps are repeated:

a. DCT coefficients are computed for the block.

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b. Fusion rules are applied to obtain fused DCT coefficients.

c. The fused image is obtained by performing the inverse discrete cosine transform (IDCT) on the combined high and low-frequency coefficients. The general equation for a 2D DCT, applicable to an N by M image, is defined as follows Eq(1), Eq(2):

$$F(u.v) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \left(\frac{2}{M}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \Lambda(i).\Lambda(j).cos\left[\frac{\pi.u}{2.N}(2i+1)\right] cos\left[\frac{\pi.v}{2.M}(2j+1)\right].f(i.j) \quad (1)$$

$$\Lambda(\xi) = \begin{cases} 1^{\frac{1}{\sqrt{2}}} & for \xi = 0 \\ & otherwise\ 1 \end{cases} \quad (2)$$

$F(u.v)$: function of discrete cosine transform

$f(i.j)$: original function

$(u.v)$: spatial coordinates in the pixel domain (0,1,2….7)

$(i.j)$: coordinates in the transform domain (0,1,2….7)

N, M=8

Algorithms that utilize block sizes smaller than 8x8 or the same size as the image itself do not perform well. Among the basic and straightforward image fusion methods in the DCT domain, the DCT average stands out. The image fusion algorithms based on DCT and DCT max also demonstrate good performance. These simple algorithms are suitable for real-time applications[7] . When considering the DCT as a set of fundamental operations that can be precomputed and stored for a specific input array size, it becomes computationally simpler and more efficient, particularly for an 8x8 block size. In this scenario, the only values that need to be calculated are for the convolution mask (8x8 window) applied over the image, which overlaps with all rows and columns. The DCT formula easily determines these values. The advantage of the DCT technique is that it employs actual values, making it easy to design and capable of enhancing contrast. Compared to the discrete wavelet transform (DWT), the DCT is superior[11].

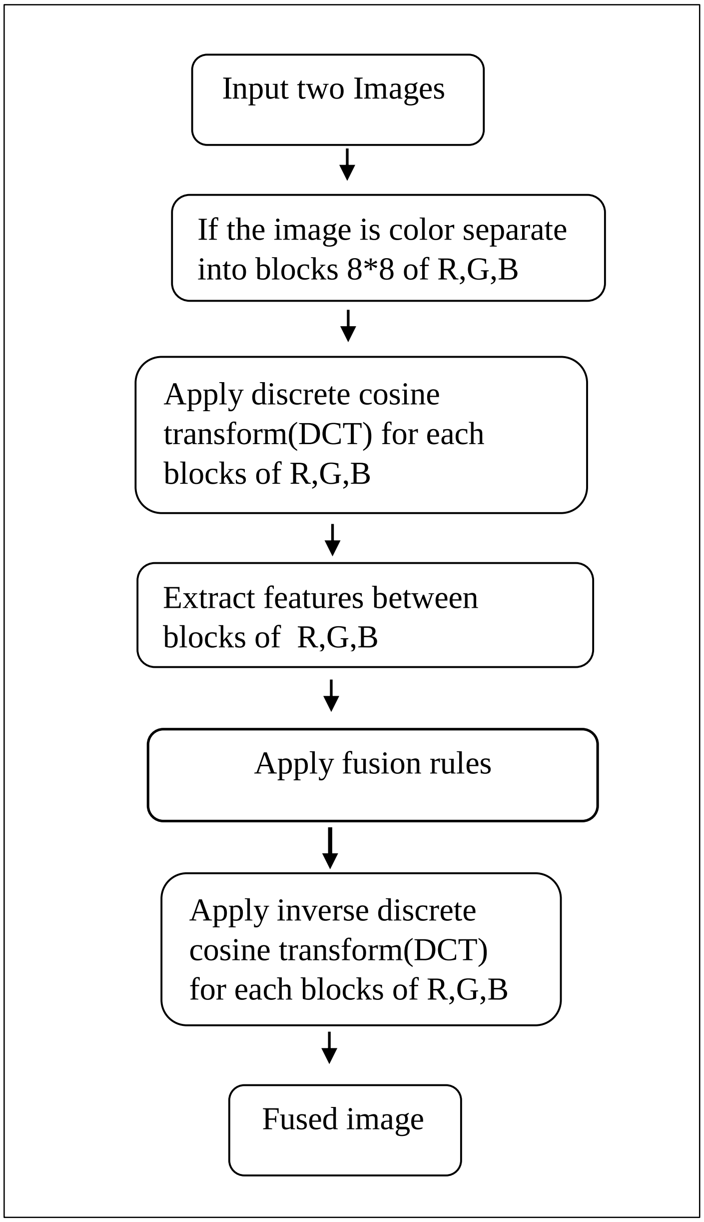

Fig. 1 Fusion based on discrete cosine transform

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3. FEATURE EXTRACTION

A variety of methods of feature Extraction, including maximum, average, brainstorm optimization, higher AC coefficient, particle swarm optimization, zeros coefficient, and positive coefficient is used to extract the distinctive properties between blocks. Feature extraction based on maximum by comparing the number of AC coefficients, negative numbers, positive numbers, variance, DC coefficients, and zero numbers in the first block of the first image with those in the first block of the second image, the maximum fusion rule is applied between blocks[12]. Feature extraction based on average by comparing the number of AC coefficients, negative numbers, positive numbers, variance, DC coefficients, and zero numbers in the first block of the first image with those in the first block of the second image, the average fusion rule is applied between blocks. Feature extraction based on brainstorm optimization The population is divided into clusters, and offspring are generated within or between clusters. The scaling factors of DCT coefficients are used for frequency-domain image fusion. Feature extraction-based Particle Swarm Optimization (PSO)- fusion method is employed to determine the appropriate weights for fusing the coefficients of each color band[13]. These optimized weighting factors are then applied to combine the DCT coefficients of visible and infrared images. Feature extraction based on zero numbers We compare the number of zeros between the first block in the first image with the number of zeros in the first block in the second image, and we perform the subtraction process between them and test them if it is less than or equal to the value of the Threshold. The rest of the non-zero coefficients are the ones in the upper left corner of the image, For Feature extraction based on positive numbers we compare the number of positive numbers between the first block in the first image with the number of positive numbers in the first block in the second image, and we perform the subtraction process between them and test them if it is less than or equal to the value of the Threshold. We apply the fusion rules, but if the condition is met, we choose the block with the highest positive numbers. This project will decrease the effort of the subsequent steps that help identify the distinctive features in the block and neglect the rest of the features[14].

4. RELATED WORK FOR IMAGE FUSION BASED ON DCT

Various feature extraction techniques are employed in fusing multiple images of the same scene into a single image with specific modifications. The literature on these techniques is included in this section.

In [15], a diverse collection of satellite images taken from a far-off distance is discussed. When capturing these images, various issues such as noise may arise. The study explores the application of DCT directly to the satellite images or after applying a Laplacian filter. The evaluation of the fusion results is based on three quantitative variables: PSNR, entropy, and mean square error. The investigation utilizes two LANDSAT multi-timespan images with a resolution of 648 x 1462 as the basis for the satellite images. The highest-value DCT coefficient is selected for fusion. The results demonstrate that fusion on filtered images produces superior outcomes compared to fusion on unfiltered images.

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In [11], a discrete cosine transform-based technique for multi-focus image fusion is developed using networks of visual sensor devices. Raw image elements are extracted and divided into 8x8 blocks. DCT coefficients are computed for each block, and the block with the highest AC coefficient value is selected for fusion. The fused image is reconstructed by applying an inverse DCT to the fusion DCT coefficients. Higher AC coefficient values imply a more diverse and finely detailed image. Performance evaluation includes metrics such as peak signal-to-noise ratio (PSNR), mean squared error, and structural similarity index. The fusion strategy avoids complex floating-point arithmetic calculations like mean and variance.

In [13], the focus is on surveillance applications where a single informative fusion image is created from visible and infrared images. The Particle Swarm Optimization (PSO)based fusion method is employed to determine the appropriate weights for fusing the coefficients of each color band. These optimized weighting factors are then applied to combine the DCT coefficients of visible and infrared images. The first fused image is created using inverse DCT. For better target detection and visual understanding, the fused image is further enhanced through adaptive histogram equalization. Evaluation of the framework includes quantitative metrics such as standard deviation, spatial frequency, entropy, and mean gradient.

In [16], the brainstorming technique for optimization is recommended. A novel global optimization method called brainstorming (BSO) is proposed. The population is divided into clusters, and offspring are generated within or between clusters. The scaling factors of DCT coefficients are used for frequency-domain image fusion, specifically for visual and thermal images. The provided images are resized to 256x256 pixels and divided into 16 non-overlapping segments. DCT is applied to each segment of the thermal and visual images. The BSO technique is employed to obtain properly weighted components, which are then used to derive the fused image F in the frequency domain. Finally, inverse DCT is applied to obtain the merged image. Evaluation of the technique involves metrics such as entropy, (N)^ABF (l)^ABF (Q)^ABF, and four other quality measures, with the brainstorming optimization strategy outperforming particle swarm optimization.

In [12], a multiple-focus watermarking method based on the discrete cosine transform is described. The fusion process consists of five steps, beginning with reading the photos and dividing RGB color images into their respective R, G, and B channels. DCT is applied to each channel, and contrast levels are established for each 8x8 block. The block with the highest contrast value in each channel is chosen for the fused image. This process is repeated for all channels. The parameter values are converted back to pixel values, and an inverse DCT is performed on each combined channel. The channels are then combined to generate the final fused image. The proposed technique is evaluated using measurement units such as standard deviation and peak signal-to-noise ratio.

In [17], the author conducted a study where multiple shots of the same subject were combined, despite the poor quality of the images. Spatial frequency and DCT were recommended for the fusion process. The images were analyzed to determine the minimum and maximum values for each. The fusion utilized max-min normalization of DCT coefficients and spatial frequency. Evaluation criteria such as PSNR, RMSE, MAD, AAD, and SSIM were used, with LYTRO datasets serving as the basis for evaluation.

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In [18], the integration of visible and infrared images is explored. Infrared radiation is chosen for its high contrast, while visual images are used for their informational richness. Existing fusion methods are inadequate for achieving this specific type of fusion. To address this challenge, the Generative Adversarial Network with Multiple Classification Constraints (GANMcC) fusion framework is proposed. GANMcC simultaneously transforms the fusion image into various distributions, effectively combining infrared and sharper images. A generative adversarial network with multiple classifications is employed to estimate the distributions of visible light and infrared fields simultaneously, achieving a more balanced representation with enhanced contrast and texture detail. The main objective of GANMcC is to gather information, allowing the generator to extract more useful information from the source images, including intensity and gradient information. Mean and standard deviation are utilized for evaluation.

In [19], a method is presented for integrating Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) in two phases for medical Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) images. The input images are divided into 8-pixel blocks, and the DCT coefficients are calculated. The first phase of fusion involves the combination of these DCT coefficients, followed by the incorporation of DWT transformation. The results demonstrate that the proposed approach performs up to 5% better in terms of fusion and overall image quality compared to single-stage DWT and DCT approaches. Evaluation metrics such as PSNR, MAE, SNR, and MSE are employed for evaluation.

5. APPLY INVERSE DISCRETE COSINE TRANSFORM(IDCT)

The inverse discrete cosine transform (IDCT) converts a data representation that is better suited for compression into an image in the spatial domain. It is the reverse operation of the discrete cosine transform (DCT), where the IDCT function recovers the original image from the DCT coefficients[20].

$$f(x.y) = \frac{1}{4}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} c(u\,)\,c(v)F(u.v)\,cos\left[\frac{\pi.u}{2.N}(2x+1)\right]cos\left[\frac{\pi.v}{2.M}(2y+1)\right] \quad (3)$$

$$c(u) = \begin{cases} \frac{1}{\sqrt{2}} & for\; u = 0 \\ & otherwise\;\; 1 \end{cases} \quad (4)$$

$$c(v) = \begin{cases} \frac{1}{\sqrt{2}} & for\; v = 0 \\ & otherwise\;\; 1 \end{cases} \quad (5)$$

$f(x.y)$: function of inverse discrete cosine transform

$F(u.v)$: function of discrete cosine transform

$(x.y)$: spatial coordinates in the pixel domain (0,1,2….7)

$(u.v)$: coordinates in the transform domain (0,1,2….7)

N, M=8

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6. FUSED IMAGE

Image fusion combines two registered images of the same object into a single image that is more easily interpreted than any of the originals[14]. The steps are shown in Fig(2).

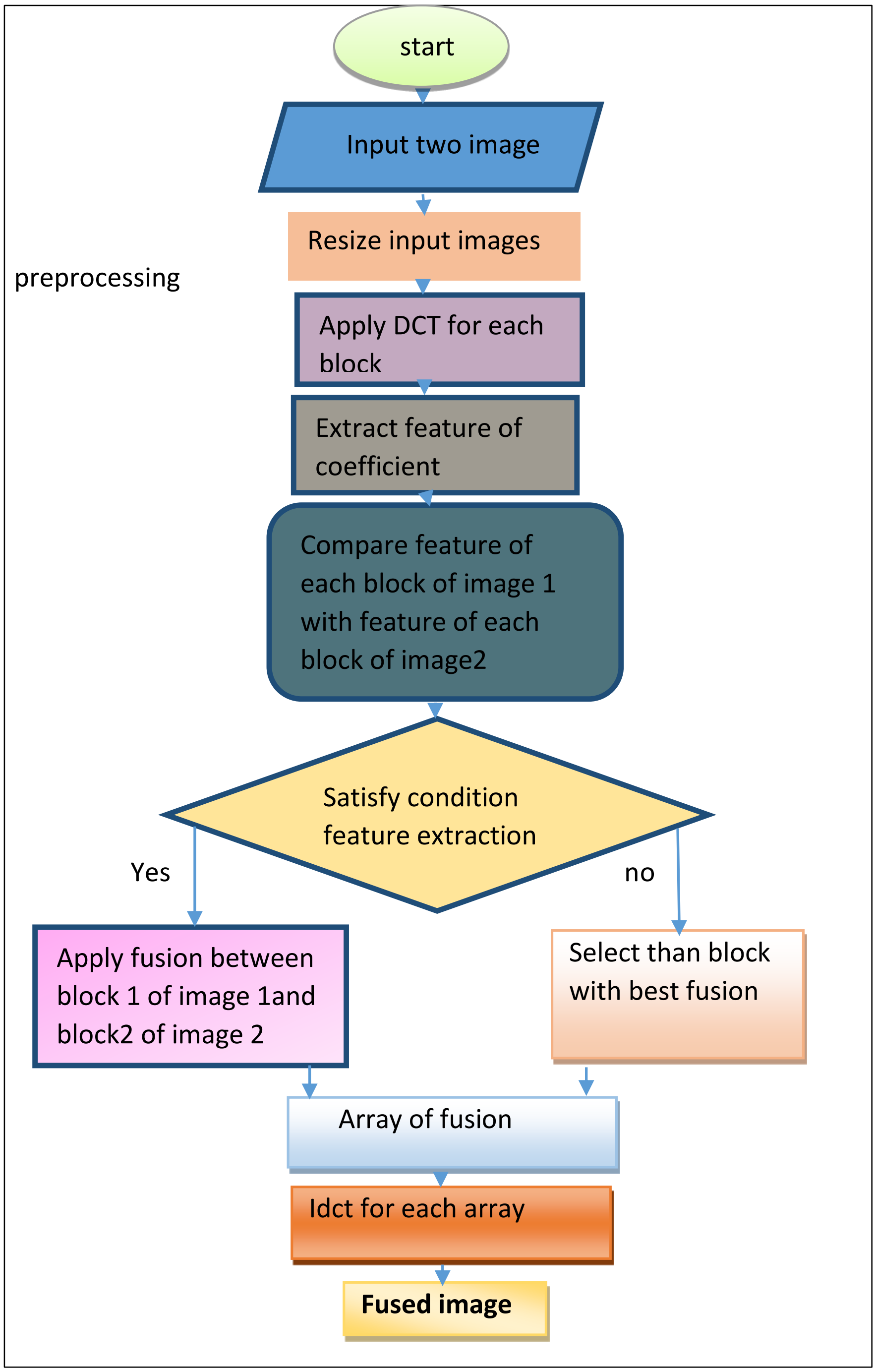

Fig. 2 Fused image steps

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7. COMPARE IMAGE FUSION TECHNIQUES

TABLE I Advantage and dis advantage of image fusion techniques

Techniques	Advantage	Disadvantage
Pixel-Level Fusion[21]	Simple to implement and keeps all of the original pixel data.	It might not be appropriate for many applications due to the limited ability to capture complicated correlations between images.
Wavelet Transform-Based Fusion[22]	offers multi-resolution fusion, which is good for maintaining details and cutting down on noise.	possible artifacts, difficulty in selecting wavelet functions and decomposition levels.
Principal Component Analysis (PCA)[23]	Effective dimensionality reduction improves contrast and visual appeal.	Due to picture registration sensitivity, not all pertinent information may be captured.
Intensity-Hue-Saturation (IHS) Transform[24]	suited for conserving color information while improving spectral information.	loss of spatial detail and fusion artifacts.
Sparse Representation-Based Fusion[25]	Compressive sensing is effective for capturing complex picture interactions.	requires a solid background in mathematics and can be computationally demanding.
Machine Learning-Based Fusion (e.g., Deep Learning)[26]	can pick up on complicated visual correlations and is very flexible to different uses.	requires a lot of computer power, training data, and knowledge.
Fuzzy Logic-Based Fusion[19]	efficient at handling ambiguity and uncertainty in visual data.	The design of complex algorithms is sensitive to parameter selections.
Decision-Level Fusion[27]	brings together judgments from several picture sources, appropriate for categorization problems.	requires clearly defined decision-making processes; not all fusion scenarios may be appropriate.
Discrete cosine transform[28]	enhanced visualization, better decision-making, robustness, and improved information	Variability and Subjectivity

In this research, the focus will be on the technology of image fusion based on the discrete cosine transform, as it improves the quality of the images in addition to producing an image that includes all the important information.

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8. EVALUATION METRICS

There are multiple factors to consider when assessing the produced image, with the primary emphasis placed on the following criteria[29] :

1) Structural Similarity Index Measure (SSIM): The structural similarity index measure (SSIM) is a technique used to predict the perceived quality of various digital images and videos, including those in the domains of digital television, film, and other types of visuals. SSIM provides a means to quantify the similarity between two photos.

2) Peak Signal to Noise Ratio (PSNR)

When the fused and reference images are the same, PSNR will be high. A higher score indicates improved fusion.

3) mean square error (RMSE)

It is calculated as the product of the equivalent pixels in the reference image Ir and the fused image If's root mean square error.

4) Mean absolute error (MAE)

The relevant pixels in the reference and fused images have a mean absolute error.

5) Signal-to-noise ratio (SNR)

When the reference and fused images are identical, this measure will be high. Better fusion is implied by a higher value.

6) Standard deviation (σ)

In the combined image, it assesses the contrast. The standard deviation of an image with great contrast would be considerable.

7) Entropy (EN):

Entropy is a metric for gauging an image's information density. Noise and other unwelcome fast variations can affect entropy. A picture with a lot of information would also have a lot of entropy.

8) Special Frequency(SF):

Its spatial frequency represents the level of overall activity in the combined image.

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TABLE II Comparative Study Analysis Discrete Cosine Transform Coefficient Feature Extraction

Research	Methods	Dataset	Metrics				
Y. A. V. Phamila and R. Amutha in 2013.[7]	Higher AC of DCT coefficient	Lena image	MSE	PSNR	SSIM		
			0	∞	1		
N. Paramanandham and K. Rajendiran In 2018.[8]	Particle swarm optimization of DCT coefficient	Car image		MG	SD	SF	E
			Without CLAHE	3.10	21.2	7.74	5.31
			With CLAHE	14.65	37.3	23.3	7.02
A.Asokan and J. Anitha In 2019.[6]	Maximun DCT coefficient	LANDSAT satelite images	Sample	PSNR	MSE	Entropy	
			Without filter	29.399	74.262	4.2692	
			With filter	36.621	26.810	4.271	
M.H. Alkawaz, A. Rehman, A. S. Almazyad, and T. Saba in 2016.[10]	Spatial frequency of DCT coefficient	Clock image	SD				
			6.4266				
Vakaimalar E, Mala K, and Suresh Babu R in 2019.[11] .	Spatial frequency of DCT coefficient	Lytro dataset	PSNR	SSIM			
			41.5544	0.9641			
J. Ma, H. Zhang, Z. Shao, P. Liang, and H. Xuin 2020.[12]	GANMcC	TNO dataset	Standard derivation				
			0.173				
		Road scene	0.329				
E. AMİRİ, H. YAZDANİ PRAEE In 2021.[13]	Maximum of DCT	150 image	PSNR	MAE	SNR	MSE	
			42.1	13.99	48.6	13.002	
	Average of DWT	Each group (50)	42.01	13.03	48.61	13.06	
			42.21	13.87	48.59	13.009	

Table II shows previous studies of image fusion based on discrete cosine transform. It also explains the methods used to extract important transactions discrete cosine transform. It also explains the result using specific evaluation metrics.

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9. CONCLUSION

In conclusion, the image fusion technique that utilizes the Discrete Cosine Transform (DCT) has proven to be highly effective in combining multiple images. The fused image combined all the important information in both images. The quality of the resulting image is superior to the quality of the input images. This one image has all the relevant information and is more accurate and informative than any image from a single source. The resulting image is more suitable and understandable for human and machine perception

Conflict of interest.

There are non-conflicts of interest.

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الخلاصة

المقدمة: دمج الصور على أساس تحويل جيب التمام المنفصل (DCT) هو طريقة مستخدمة لدمج صور متعددة في صورة مركبة واحدة. تعمل هذه التقنية على تحسين الجودة المرئية واستخراج المعلومات القيمة من الصور المدخلة.

طرق العمل: تحويل جيب التمام المنفصل (DCT) هو تقنية تحويل مستخدمة بشكل شائع في معالجة الإشارات وضغط الصورة. إنه يوفر وسيلة لتمثيل صورة فيما يتعلق بمكونات التردد الخاصة بها.

الاستنتاجات: الصورة المدمجة جمعت جميع المعلومات المهمة في كلتا الصورتين. جودة الصورة الناتجة تتفوق على جودة الصور المدخلة. تحتوي هذه الصورة الواحدة على جميع المعلومات ذات الصلة وهي أكثر دقة وغنية بالمعلومات من أي صورة من مصدر واحد.

الكلمات المفتاحية: دمج الصورة ، استخلاص الميزات ، DCT ، الصورة المدمجة ، تقييم الأداء