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Silhouette vanished contour discovery of aerial view images by exploiting pixel divergence

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ABSTRACT

An image's edge detection is the process of finding and pinpointing sharp discontinuities in an image. Detecting the edges of an image significantly reduces the quantity of data and removes unnecessary information while keeping the fundamental structural aspects of an image. Edge detection is essential when it comes to image categorization in computer vision and object identification. The primary goal of this research is to investigate several strategies for edge detection and shadow of objects in aerial view images. Machine vision, face detection, medical imaging, and object detection are just a few examples of applications where image segmentation has been widely utilized. Image segmentation is categorizing or identifying sub-patterns in given an image. Many algorithms and strategies for picture segmentation have been presented to improve segmentation issues in each application area. Techniques such as threshold-based and region-based picture segmentation were used in this study. An edge detection method such as Sobel, Prewitt and Roberts and the Canny approach is applied to the benchmark image and compared with the proposed octagonal pixel divergence edge detection (OPDED) algorithm. Results show that the proposed approach is more effective than the other methods, with a quality image with edges.

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1. INTRODUCTION

Step edge detectors [1], have been a key component of many computer vision systems for many years. In addition, edge detection decreases the quantity of data that must be processed while keeping important structural information about object boundaries. Although many are thought to have common requirements, a vast variety of edge detection applications each have their own unique set of possible outcomes. Because of this, a problem with abstract edge detection arises, the solution to which may be applied to any of the initial problem areas. For the past decade, X-rays have been routinely used for non-invasive industrial detection [2]. Computable tomography and digital radiography (CTD) methods are also frequently used in a broad range of applications ranging from diagnosis of fractures to finding out about defects in items [3]. A high-quality operator with extensive training and expertise is required for such treatments, which are pricey.

Several mathematical approaches may be used to find the areas in an image where brightness changes sharply or, more formally, where there are discontinuities. In the age of computer vision, edge detection is a procedure that may provide the significant pixel values for recognizing the overview of an image for further processing to complete applications. These values can accommodate the discontinuities.

Edges are vital points because they correspond to geometric or physical variations in item shape or size. Light and surface reflections generate perceptible changes in physical areas, affecting the texture, colour, and intensity, among other factors. In low-level image processing, edge detection is considered straightforward, despite the huge edges required for higher-level processing [4]. Demonstrated many sorts of edges with my passport-sized photograph, such as the roof, line, step, and ramp edges illustrated in Figure 1. Pixel shading is a common technique in digital image processing [5]. Some computer and robot vision applications include image segmentation, feature description, pattern recognition, image restoration, object tracking, and image compression. Even though aerial images have expanded in this field of remote sensing, various problems impede information extraction, one of which is shadows. Shadows [6] are a typical cause of remote sensing misclassification errors.

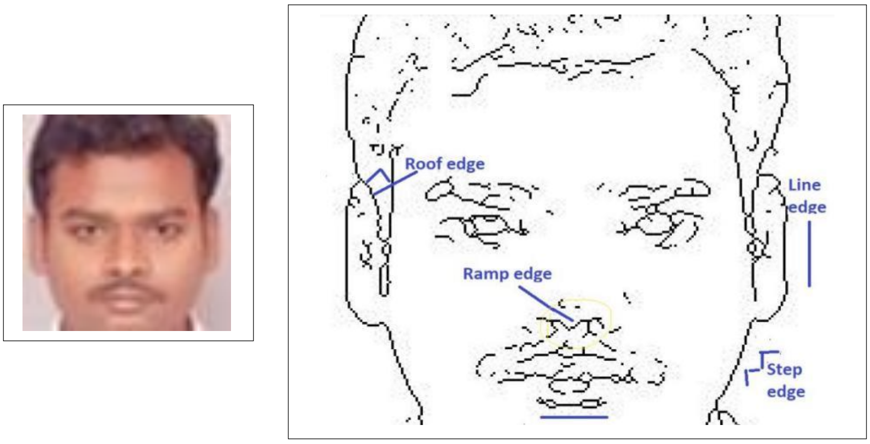

Figure 1. Identification of typical edge types in an image

There will be a significant change in visual intensity called an edge between two distinct objects in a picture. Detecting an object's edges in an image is known as edge detection It detects brightness discontinuities or quick changes in pixel intensity to determine object boundaries. By retaining critical information about object forms, the edge representation of an image minimizes data processing. Numerous object identification methods for computer vision and other image processing applications can leverage this visual description. Several studies have been done on edge detection during the previous three decades to get the perfect edge line. There is no generic performance measure for edge detection. The efficiency of this approach is usually subjective and very context dependent. Edge detection needs a narrow, speckle-free line.

In general, there are three phases in an edge detection technique. The first phase is noise reduction. Image noise should be reduced to increase edge recognition. Since additive noise is commonly a high-frequency signal, it is often reduced using a low-pass filter. High-frequency pulses can eliminate edges simultaneously. It's common to utilize a parameter to ensure noise reduction and edge information are maintained. In the second stage, a differential operator or high-pass filter is used to identify the edges. Lastly, an edge localization approach is used to distinguish between real edges and noise-induced similar responses.

Edge detection may be grouped into spatial, frequency, or wavelet. Pixel-by-pixel, the spatial domain, performs gradient operations on the images. Roberts, Prewitt, and Sobel are first-order edge detectors, whereas Laplacian, Gaussian-Laplacian, and Canny are second-order edge detectors. The canny edge detector has been a standard for many years and has the finest performance. The canny technique uses the entire picture data to compute high and low thresholds to accomplish hysteresis thresholding. Canny edge detection is computationally more demanding than other methods, such as Roberts and Sobel, because of this, and it also demands extra image-wide pre-processing calculations.

2. RELATED WORK

Edge continuity was also a major focus of Heric and Zazula [7], who employed, instead of using a local detector, computational models are used to examine the edges in their datasets. A signal registration-based edge-to-contour line connection was developed to minimize the occurrence of edge discontinuities and calculate a confidence index for contour connections. Shih and Tseng [8] used gradient-based edge detection and wavelet-based multi-scale edge tracking for the purpose of edge extraction. The edge tracker uses a suggested contextual filter to refine the identified edges in multi-scale gradient pictures. It was proposed by Liang and Looney [9] that a competitive fuzzy edge detection method be developed. Fuzzy classifiers based on extended ellipsoidal Epanechnikov functions were used to classify image pixels into six different categories: background (no edge), speckle (noisy edge), and four different kinds of edge (in four directions). An innovative neural network design was developed by Chang [10] to identify the edges of objects. contextual hopfield neural networks (CHNN) is a method he developed for determining the boundaries of medical computed tomography (CT) and magnetic resonance imaging (MRI) image.

An overview of methods for identifying and categorizing edges in colour images was presented by Koschan and Abidi [11]. Although edge detection in grayscale pictures is well-known, it has gotten less attention in colour images. When comparing colour pictures with gray-level photos, the most significant distinction is that a colour vector (containing three components) is allocated to each pixel in a colour image. Still, a gray-level vector is given to each pixel in a grey-level image. Scalar image functions have been replaced with vector-valued image functions for colour image processing. Zhu [12] proposed a new technique to edge identification based on image fusion and multi-structure element morphology. Structural element orientations, where all structural components' direction angles are 0^o, 45^o, 90^o and 135^o are used to identify edges, and the final edge result is generated via entropy weighted image fusion. The proposed method may achieve noise reduction and edge information preservation.

See and Khuehiang [13] developed an neural network based edge detection technique published in nature scientific computing. In a neural network, processing modules are grouped into layers and connected in a network. Forcing the neural network to generate an individual output in response to a specific input is accomplished by using supervised or unsupervised learning methods to train it. Bai *et al.* [14] described a novel morphological technique for noise reduction and edge detection in binary and grayscale pictures. Using the Sobel edge detection operator and the soft-threshold wavelet denoising, we reduced the amount of noise in the image. On images containing Gaussian noises, Gao *et al.* [15] suggested an edge detection approach. According to Priyadarshini and Sahoo [16], there is a novel way to identify small edges using fundamental mathematical operations like additions and divisions. Zhang *et al.* [17] proposed a technique based on gray level integer logarithm ratios for using a grey level difference between two successive image points to indicate the variability in grey levels. They advised using a grey level ratio between two image points instead.

Shankar *et al*. [18] recognized several items rapidly 0^o, 45^o, 90^o and 135^o and reliably, making it one of the most efficient ways to detect a wide range of objects available today. Gupta *et al.* [19] proposes an adaptive thresholding-based wavelet denoising approach correlated by innovative social group optimization (SGO) and accelerated particle swarm optimization (APSO). This framework was designed using MATLAB coding, and the analysis was carried out with the aid of image property metrics such as peak signal to noise ratio (PSNR), mean square error (MSE) and other structural similarity index metrics (SSIM). Valasek *et al.* [20] was done their worked-on vision-based sensor and navigation system to improve the performance. Shankar *et al*. [21] used various characteristics, such as leaves and grass, to identify some objects. Colour, shape, texture, petals, sepals, and other conventional identifying characteristics sort flowers into several classifications. With the use of deep learning, picture analysis and categorization have been greatly improved. Shankar *et al*. [22] usedawide range of industries, including astronomical photography, electronic microscopy, and video surveillance, to have benefited from picture colourization. Deep learning algorithms are used to create an automated method for colour grayscale images.

Wang *et al*. [23] proposed casting which oriented bounding boxes (OBBs) regression as a center-probability-map (CenterMap)-prediction issue, removing ambiguity on target definitions and backdrop pixels. After then, the projected CenterMaps are put to use in the process of creating the OBBs. The CenterMap OBB depiction is straightforward, yet it achieves its intended purpose. In addition, a weighted pseudo-segmentation-guided attention network is used to provide the object-level characteristics for predicting the horizontal bounding boxes and the OBBs. This helps to better differentiate the intriguing objects from the cluttered background.

Babu *et al*. [24] claimed that the most expressive method for humans conveys their emotions to enhance facial expression identification by using a method of two-dimensional (2D) image processing for feature extraction and a neural network-based decision tree to recognize more complex facial expressions. The technique performs pre-processing steps before dividing the picture into two major sections (eyes and mouth) and drawing Bezier curves for the main portions. Xia *et al*. [25] provides a large-scale dataset for item detection in aerial photos to develop earth vision, also known as earth observation and remote sensing (DOTA). To achieve this goal, acquire 2806 aerial photos using a variety of sensors and platforms. Each image is roughly 4000-by-4000 pixels in size and includes objects that display a wide range of scales, orientations, and shapes. After that, specialists in aerial image interpretation annotate these DOTA photos using 15 different object categories that are typically used. Mnih and Hinton [26] considered the challenge of learning to categorise aerial photos based on previously created maps. They gave a plentiful supply of labels; however, the labels themselves are frequently missing information and frequently have poor registration. They propose two robust loss functions for dealing with label noise and train a deep neural network on two tough aerial picture datasets. The robust loss functions increase performance, and our top system outperforms the best published results on the challenge.

Mittal *et al.* [27] investigated two important pitfalls faced in detecting edges: connectivity and thickness of edges in any computer vision application optimal threshold value affecting the edge detection. Thus, they proposed a robust edge detection methodology supporting multiple threshold approaches named B-Edge and it is used to overcome those pitfalls. They also try to identify the limitations of the Canny edge operator. This method operates on triple thresholds that aim to solve the significant issues with image contrast, pixel selection, error management, and matching the ground truth for edge detection Su *et al.* [28] in this recent era. Deep convolutional neural network (DCNN) can obtain human-level performance in detecting edges by consuming the rich and abstract edge representation capabilities with the pre-trained convolutional neural network (CNN) backbone by drinking a lot of energy and memory. They considered traditional edge detectors, like Canny, Sobel, and local binary pattern (LBP), are not often examined in the often-improvement of deep learning era.

Versaci and Morabito [29] proposed a technique based on an approach for fuzzy edge detection in which fuzzy divergence formulation is exploited without specifying the threshold application. Thus, they proposed a new fuzzy-based edge detector in addition to all and fuzzy entropy minimization. Al-Amaren *et al.* [30] proposed techniques for edge detection based on visual geometry group 16 layers (VGG16) presented with a lesser level of complexity. This strategy has considerably improved the performance of picture edge identification approaches by overcoming the constraints of CNNs. A novel VGG16-based DCNN approach for edge detection is developed utilizing the residual learning mechanism to outperform other similar networks while maintaining their low complexity. Huan *et al.* [31] came up with a way to trace a crisp edge detection with deep edge detectors that considered the context. New tracing loss for feature unmixing and context-aware fusion block for side mixing are two modules of the context-aware tracing strategy (CATS). Their findings reveal that the proposed CATS may be applied to current deep edge detectors to improve localization accuracy. Chetia *et al.* [32] present an improved quantum representation technique and devise a quantum enhanced. Sobel edge detection algorithm that incorporates non-maximum suppression and double threshold methods for a unique enhanced quantum representation method.

To identify the objects in the aerial view images automatically by machine vision. Due to this computer needs so much of time to process lot of image data in the images. Thus, it will take more response time to identify the objects in that image. Therefore, to reduce the time complexity, we need to reduce the image data for processing to identify the objects in that image. So, one of the approaches is edge identification of image. But remote sensing images also contain shadow of objects. This shadow should mislead the identification of objects using edges. So, we need to focus on to remove shadow of objects in the images and fulfil to identify the quality of edges for object detection.

3. METHODOLOGY

This proposed method is used to remove the shadow of objects in the aerial view images and used to identify the original edges of objects instead of shadow. Here shadow detection and darkness is eliminated for objects in the images by using red green blue (RGB) intensities variation and threshold filtering. Here the picture is considered as M×N sized (M rows and N columns) image array as shown in matrix form in Figure 2 for pre-processing image. The typical 3×3 kernel of an 8-neighbourhood pixel is shown in Figure 3(a), and the edge detection is based on gradient descent values of each pixel in the grayscale level image 3×3 kernel mask is shown in Figure 3(b).

P_{11}	P_{12}	P_{13}	..	P_{1N}
P_{21}	P_{22}	P_{23}	..	
P_{31}	P_{32}	P_{33}	..	
P_{41}	P_{42}	P_{43}	..	
..	..	..	..	
P_{M1}	..	..	..	$P_{.M.N.}$

Figure 2. M×N sized image as array in matrix form

P (x-1, y-1)	P (x-1, y)	P (x-1, y+1)
P (x, y-1)	P (x, y)	P (x, y+1)
P (x+1, y-1)	P (x+1, y)	P (x+1, y+1)

(a)

-1	-1	-1
-1	+ 1	-1
-1	-1	-1

(b)

Figure 3. A typical 3×3 mask for pixel position in (a) 8-neighbour pixels and (b) proposed kernel

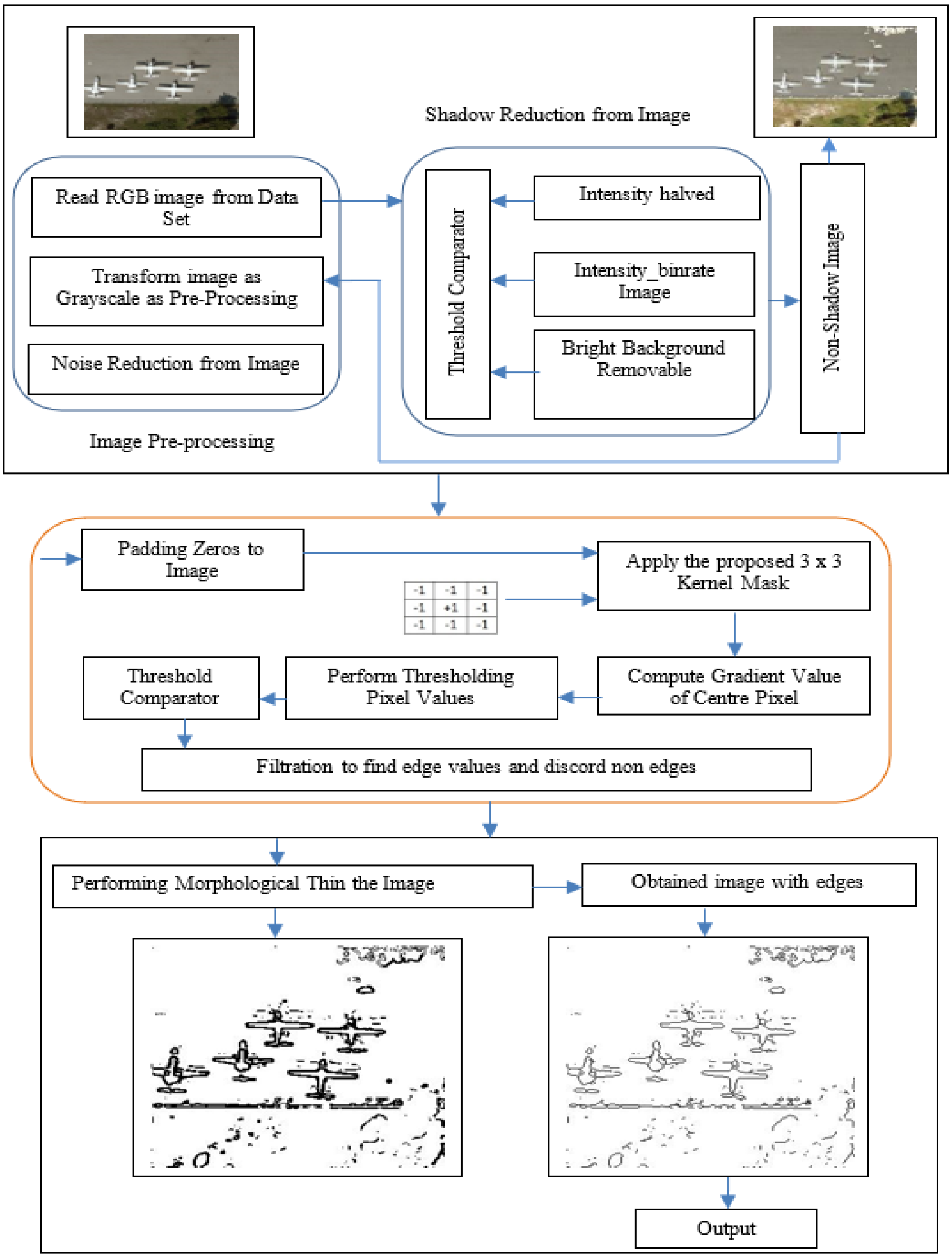

Figure 4. Flow of proposed work

3.1. Proposed algorithm

In this section, we have shown the octagonal pixel divergence edge detection (OPDED) method that we have described as Algorithm 1. This algorithm takes an RGB image as its input and produces a grayscale image with edges as its output. We can generate the edges of the shadow contained in the remote sensing images by utilizing this approach.

ALGORITHM 1*:* Octagonal pixel divergence edge detection

Input: *RGB image*
Output: *Gray scale image with Edges*
IMG-DS: *Image Dataset*
Step 1: Load an image from the respective class from the pattern dataset as image dataset (IMG-DS) {I1, I2,., IN }

$$\mathrm{Ip(x,y)} \text{€ M x N size pixels } i.e. \text{ M rows and N columns} \tag{1}$$

Step 2: Shadow Detection and Darkness Removal for the objects in the image using intensity variance and threshold bounding

$$\mathrm{B(x,y)} \text{ € } \mathrm{Ip(x,y)} \tag{2}$$

$$\mathrm{I} = \text{Convert image to } 8 - \text{bit unsigned integer arrays} \tag{3}$$

$$\text{intensity\_original} = \mathrm{I} \tag{4}$$

$$\text{intensity\_halved } = \frac{\mathrm{I}}{2} \tag{5}$$

$$\text{intensity\_binrate} = \mathrm{I} * 2 \tag{6}$$

$$intensity\_coupled = \text{intensity\_binrate} \tag{7}$$

Bright background removal: Repeat this process for every pixel in an image

$$\begin{gathered} if\,(\text{Intensity\_binrate (channel1(R))} >= 250 \ or \\ \text{Intensity\_binrate (channel2(G))} >= 250 \quad or \\ \text{Intensity\_binrate (channel3(B))} >= 250) \ then \\ \text{Intensity\_binrate (channel1(R)}\, is\ Zero, \text{channel2(G) } is\ Zero, \text{channel3}(B) \ is\ Zero) \end{gathered} \tag{8}$$

Shadow part Removal: Iterate this computation until no more pixels in an image

if (intensity_original(channel1(R)) ≤ 121 &&
intensity_coupled(channel1(R)) >= 11)
then intensity_original((channel1(R)*is Zero*, channel2(G) *is Zero*, channel3(*B*) *is Zero*)
intensity_difference = intensity_original − intensity_halved

$$\text{Darkness\_removed\_image} = \text{intensity\_original} + \text{Intensity\_binrate} \tag{9}$$

Step 3: Transform to a Gray scale image.
Step 4: Remove noise from the Original Image using the median filter
Step 5: Normalize the image pixel values by using function *d(u,v)*
Step 6: Apply step 5 to each pixel in a 3 x3 neighborhood.
Step 7: if the gradient of pixel value **>** $T_{threshold}$ (Global image threshold using Otsu's method), keep the edge; otherwise, discard the edge.

$$\mathrm{d(u,v)} = \text{maximum(gradient of pixel value, } T_{threshold}) \tag{10}$$

Step 8: Finally, the morphological thinning operation is applied to the image
Step 9: Output of the image is generated with discarded shadow and quality of edges

3.2. Explanation

Initially, select an image from the corresponding category of image data set. Here we considered PattenNet dataset IMG:DS {I1, I2,….., IN} and consider the image as I_p of M rows and N columns which is loaded into the operational set for performing segmentation operations for edge detection by evaluating (1). The shadow image of dark area will be removed by using intensity of images as per (4) and (5). To filter the pixel intensity using threshold bounding, we must convert, the image into 8-bit unsigned integer arrays as shown in (3). Darkness is removed from the image as per in (2) and by using (9). With the help of bright background removal part as per (8), (7), and (6) RGB image is converted to a grayscale level, and the global image threshold using Otsu's method is calculated by using (11).

$$T_{threshold} = \text{round(graythresh(Darkness\_removed\_image)*100)} \tag{11}$$

Now, to reduce the noise from the image, we have to use the most popular order statistic filer called a median filter and normalize the image pixel values by computing the variation of the centre pixel with its surrounding pixel in all directions as an 8-neighbourhood pixel relationship with arithmetic progression of d(u,v) as shown in (12), and it was defined as:

$$d(u, v) = \sqrt{\sum_{x=1,y=1}^{M,N}(u - v)} \quad (12)$$

u: u_{xy} x: 1 to M rows, y: 1 to N columns and v: v_{xy} x: x-1, x & x+1, y: y-1, y & y+1

Convolute each pixel in the image is computed as per (12). From this edge detection was computed by using (10). After thresholding, the grey level intensity of an image is forward to thinning the image by applying a morphological thinning operation on the image. And the final step is to achieve the images with the quality of edges without shadow edges.

4. RESULTS

In this section, the performance evaluation of the proposed approach is implemented and examined by a sequence of experiments on various images and PatternNet [33] dataset. All the experiments are carried out on Intel(R) Core (TM) i7-6500U CPU @ 2.50GHz 2.59 GHz and 16 GB RAM (random-access memory) processor. The proposed method OPDED is tested on remote sensing images and a well-known Lena image. In this process, shadows of objects in the picture are detected using different intensity operations of the image, as shown in step 2 of the proposed algorithm, bright background of the image with before shadow and after shadow removed image with noise is as shown in Figures 5(a) and 5(b) and before and after reduction of noise is as shown in Figures 5(c) and 5(d). At an earlier stage, the input image is loaded which is depicted in Figure 6(a) and processed by using an arithmetic progression of threshold values. Thus, further it leads to intensity halved and intensity binary images which are depicted in Figures 6(b) and 6(c), respectively. Then the next level image is further processed to remove the shadows of objects present in the image and result generated and displayed as shown in Figure 6(d), followed by bright background result shown as Fgure 6(e) and finally shadow free image is produced and displayed as shown in Figure 6(f).

(a) (b) (c) (d)

Figure 5. Process of shadow detection and darkness removal: (a) image with shadow, (b) shadow removed image with noise, (c) shadow and noise removed image, and (d) RGB to gray scale image

Following the removal of the shadow from the image, the next step is to remove the noise from the image using median filters and then convert that image from RGB to grayscale level image, as shown in the Figure 6. At this point, our suggested approach is applied to each pixel of the image as the kernel masking operation modifies its intensity values, and the output of this image is shown in Figure 7 as an image without the threshold comparator operation. In this case, the threshold plays a critical role in identifying the edges and distinguishing them from the non-edges. In this regard, see Figures 7(a) and 7(b) as before and after thresholding the image. Finally, a morphologically thinning operation is performed, resulting in a picture with the finest edges, as illustrated in Figures 7(c) and 7(d) below before and after the thinning process.

The proposed approach is compared with Canny edge detection, Sobel edge operator, Prewitt edge operator and Robert's edge operator. Therefore, the proposed approach achieved the best performance for remote sensing pictures with shadows than the Canny algorithm. However, Prewitt, Robert and Sobel's operator performed the best time complexity, but some edges recognition is missing from the proposed approach. The comparison of computational time of the proposed approach, Canny, Prewitt, Robert and Sobel, is summarized in Table 1, and the graph is furnished in the below Figure 8.

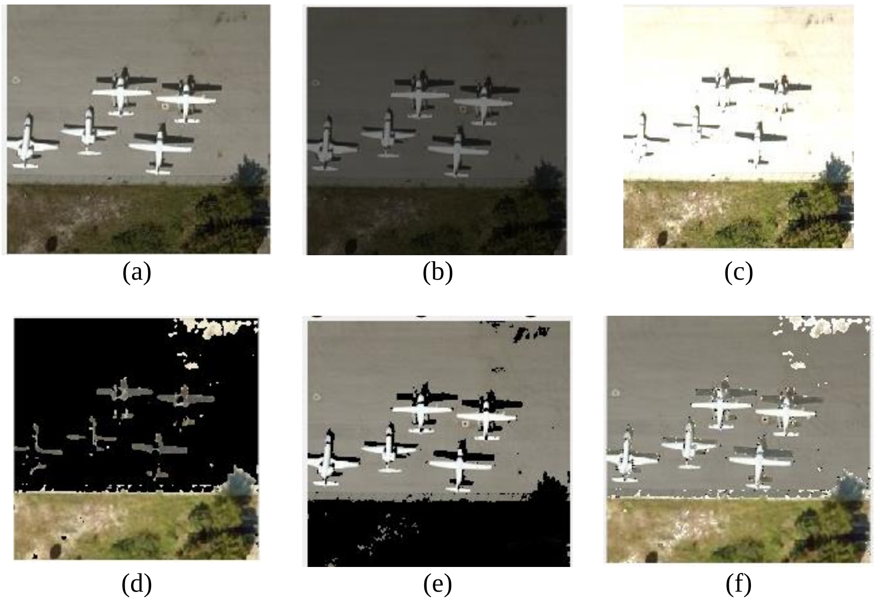

Figure 6. Process of noise reduction in an image shown as (a) original image, (b) intensity halved, (c) intensity binared, (d) shadow objects, (e) bright background, and (f) most accurate result

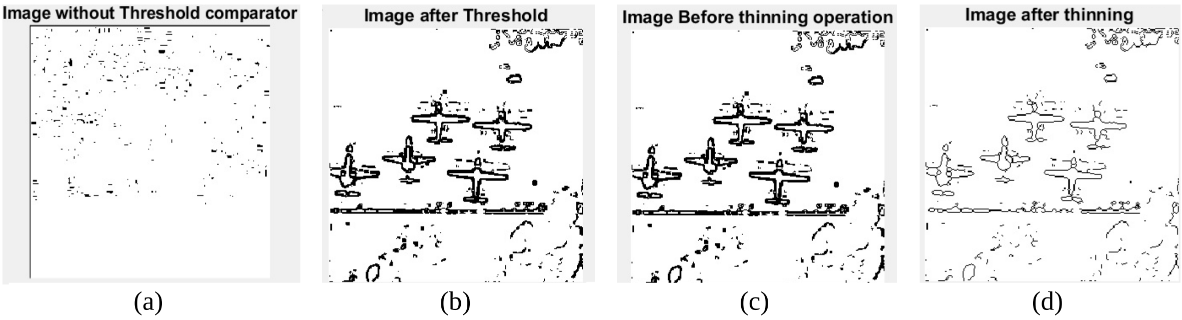

Figure 7. Process of shadow detection and darkness removal in an image as (a) image without threshold comparator, (b) after threshold, (c) before thinning operation, and (d) after thinning

Table 1. Computational speed of reported and proposed edge extraction methods

Method image type	OPDED (ms)	Canny (ms)	Prewitt (ms)	Robert (ms)	Sobel (ms)
Airplane1	0.0194	0.1589	0.0211	0.0900	0.0053
Airplane2	0.0376	0.0568	0.0023	0.0040	0.0022
Storage_room	0.0248	0.0252	0.0024	0.0059	0.0022
Lena	0.0221	0.0147	0.0026	0.0057	0.0038

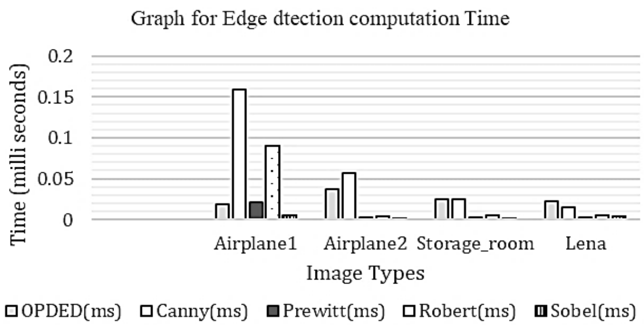

Figure 8. Graph for edge detection computation time

In Figure 9, the testing images are furnished with edge images (i) and (ii) airplane, (iii) Storage_room (iv) Lena. The resultant images are furnished as (a) proposed algorithm, (b) Canny, (c) Prewitt, (d) Robert, and e) Sobel operators. Among five approaches, the proposed methodology performed best edge detection with the cost of time complexity. Table 1 shows that the suggested method takes less time than Canny. However, the computing time of the suggested technique is significantly longer than that of Prewitt, Robert, and Sobel. Although the processing time of the suggested technique is longer, it is acceptable owing to its overall improved performance and resilience in the presence of shadows of objects in the picture, as in remote sensing.

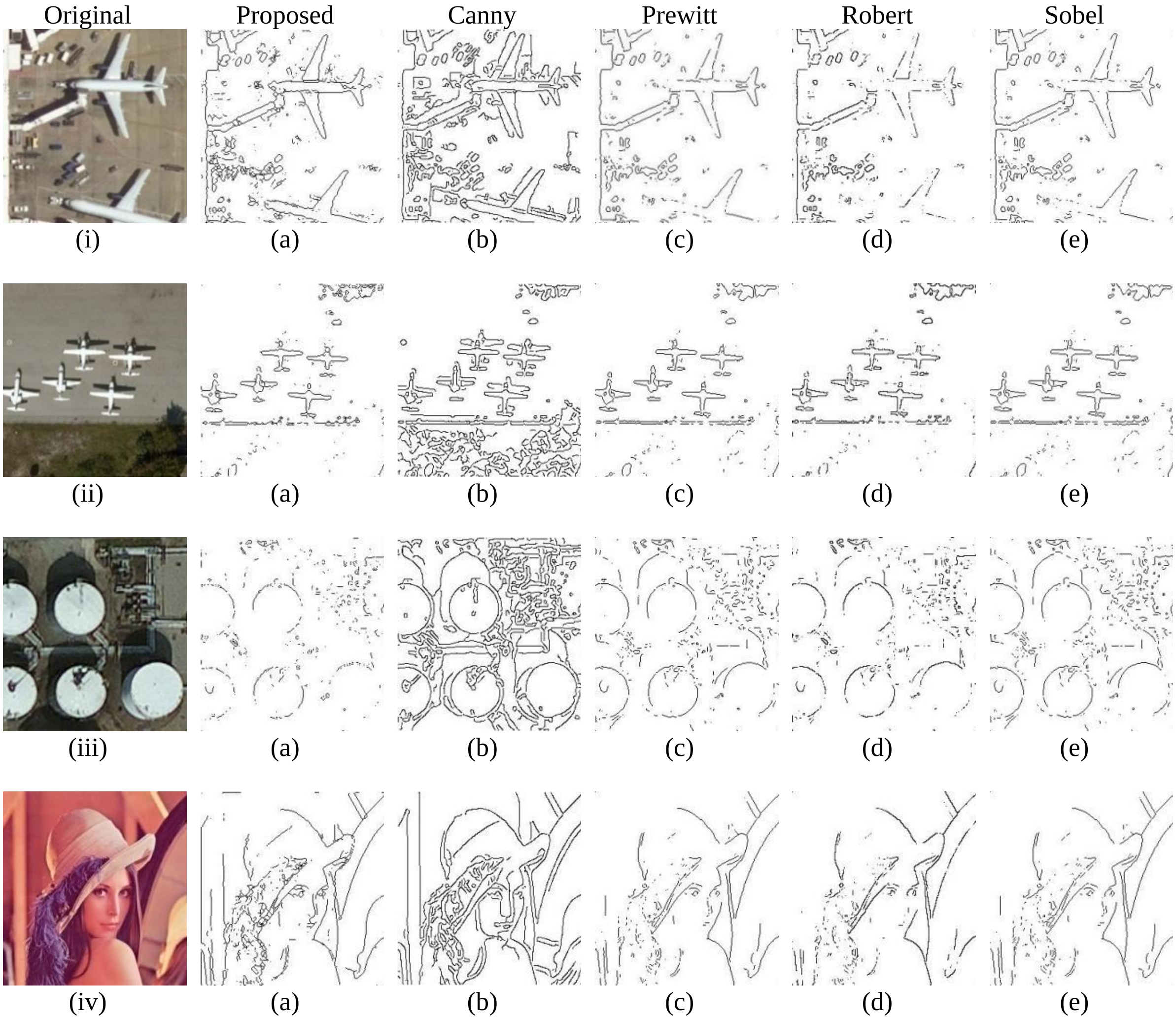

Figure 9. Comparing results of edge detection of the image types (i) and (ii) airplane, (iii) storage room and (iv) Lena, with approaches such as (a) proposed OPDED algorithm, (b) Canny, (c) Prewitt, (d) Robert, and (e) Sobel image edge detection results

5. CONCLUSION

In this research, we demonstrated the proposed approach for edge detection for a given image while considering the shadow of objects for aerial view photographs. This approach was meant to keep the key aspects of the picture after identifying the edges of the images. It is discovered that the suggested strategy outperforms the previously stated edge preservation algorithms to detect correct edges in remote sensing-based pictures with shadow and recognized as the Canny approach is unable to filters the shadow of the objects in those images. However, this strategy outperforms the others in terms of edge quality and time complexity for remote sensing images, but it takes longer time for scene images. This method is sensitive to the grayscale range's threshold value. It is necessary to develop an acceptable threshold value to build correct edges for all types of picture data sets in future work.

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