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Multi-Phase Information Theory-Based Algorithm for Edge Detection of Aerial Images

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ABSTRACT

Edge detection is the diverse way used to detect boundaries in digital images. Many methods exist to achieve this purpose, yet not all of them can produce results with high detection ratios. Some may have high complexity, and others may require numerous inputs. Therefore, a new multi-phase algorithm that depends on information theory is introduced in this article to detect the edges of aerial images adequately in a fully automatic manner. The proposed algorithm operated by utilizing Shannon and Hill entropies with specific rules along with a non-complex edge detector to record the vital edge information. The proposed algorithm was examined with different aerial images, its performances appraised against six existing approaches, and the outcomes were assessed using three image evaluation methods. From the results, promising performances were recorded as the proposed algorithm performed the best in many aspects and provided satisfactory results. The results of the proposed algorithm had high edge detection ratios as it was able to capture most of the significant edges of the given images. Such findings make the proposed algorithm desirable to be used as a key image detection method with other image-related applications.

Keywords: Aerial images, edge detection, image processing, information theory.

INTRODUCTION

With the advancement in technology, most aerial data are recorded in digital format, and virtually all image analysis and interpretation are made using digital means (Distante et al., 2020). Digital processing of images may include several procedures like formatting and data correction, enhancement to enable better visual interpretation, automated target classification, and features extraction completely by computer algorithms (Zhang, 2021). During the last decade, aerial imagery has become very useful in several fields such as mining, geography, forestry, meteorology, and weather. Aerial images have been increasingly utilized for supportable development, which is the main feature in managing natural resources, like agricultural land, forests, water, and so forth (Al-Ameen, 2020). Generally, the objects in aerial images are difficult to detect due to the complex nature of the scene being acquired (Jadhav & Patil, 2015). Aerial images contain information about different objects of interest. Edge detection approaches have been used to capture such information (Versaci & Morabito, 2021). Aerial imagery is diverse when it comes to texture as it has many kinds such as buildings, roads, lands, lakes, rivers, and so forth (Paravolidakis et al., 2018). Numerous applications are required to process grayscale and color images with the aforesaid areas, and detecting the edge of such images is required in many such applications (Aamir et al., 2019; Li & Wu, 2008; Paravolidakis et al., 2018; Samiei et al., 2018;). For instance, in image segmentation for boundary detection, coastlines extraction between sea and land regions in aerial images, detection of buildings, content-based image retrieval, and other machine vision routines (Stoian et al., 2019).

The image's edge can own various significances in different forms (Xuan et al., 2022). Consequently, numerous algorithms that work with edge recognition can identify various forms of edges and these algorithms can be considered as a distinct method depending on the ability of definition (Hait et al., 2022). Edges can own different forms; for instance, it may be a limit that separates an image region into different sub-regions, it can be a specific pixel having an intensity discontinuity, or outlines that can form the object boundaries. According to the given descriptions, the algorithms specialized in detecting the edges have different intricacy ratios, recognition abilities, and working mechanisms (Gonzalez & Woods, 2008). In aerial images, the key aim is to highlight the important features and discard the others. Furthermore, edge detection is used to provide the essential structural material of regions and objects, in that its vital duty in aerial images is to distinguish elements of interest signified by different textures via the application of suitable approaches. The main approaches of edge detection are statistical, differential, morphological, multiresolution-based, and computational intelligence (Zhou & Huang, 2001; Ye et al., 2003; Nadernejad et al., 2008; Papari & Petkov, 2011). To the given image content, the method of edge detection responds differently, and the results are different for every domain.

Many research works have been introduced in the past years for edge detection, and several of them are reviewed as presented in the related work section of this paper. This study introduces a fully automatic edge detection approach based on information theory. In this work, a combination of Shannon and Hill entropies along with certain rules will be used to filter the image information before passing it to a non-complex edge detector to extract the related edge information. The proposed algorithm is compared with various methods and the output of the comparisons is evaluated by three methods. The empirical outcomes are analyzed and deliberated, and the application abilities of the proposed algorithm are highlighted. The structure of the article is as follows: Section 2 provides reviews for the previous research works in this field. Section 3 explains the proposed algorithm in depth. Section 4 shows the implementation results of the experiments and comparisons accompanied by the required analysis. Section 5 delivers the reached conclusions.

RELATED WORKS

Many researchers have approached the field of edge detection. The work of Abdou and Pratt (1979) investigated early edge detection approaches like Roberts, Prewitt, and Sobel, which owned a somewhat similar working concept. Each method had its own distinct vertical and horizontal operators that were convolved separately to the input image. The results were obtained by raising both convolution outputs to the power of two, adding them, and then computing the square root to acquire the outcome. Laplacian operators have also been used for edge detection by Berzins (1984). To detect the edges using this approach, any one of the discrete Laplace 3×3 kernels were convolved to the image to obtain the image edges. On the other hand, Canny (1986) introduced the Canny edge detector, which was a multi-step method that first utilized a Gaussian filter to decrease undesirable information such as noise. Then, it calculated the vertical and horizontal gradients of the filtered image using Sobel operators. After that, a thresholding process was applied, followed by the suppression of non-maximum pixels to get thin edges. Finally, another thresholding process was applied, followed by an edge linking process to obtain the final output. Masoud and Bayoumi (1995) studied the Laplace of Gaussian (LoG) filter as a method of edge detection. LoG worked by convolving the Laplacian second-order filter by the Gaussian smoothing filter and the outcome of this process was convolved again with the input image to gain the outcome. These six methods are considered the classical simple edge detection methods in image processing. Tian et al. (2011) proposed a variation-adaptive ant colony optimization (VAACO) based approach, whereby it began by dispatching the ants to the input image, creating the pheromone and heuristic matrices. Next, the construction procedure commenced by choosing certain ants to move according to a certain matrix. Then, the update process was applied, followed by applying the decision process that determined the edge information to produce the output.

Years later, more advanced complex methods have been proposed for improved edge detection. Suliman et al. (2011) presented a fuzzy logic-based method, which utilized a combination of Gaussian filter, fuzzy classifier, fuzzy rules, and a set of morphological operations to obtain the desirable edges. Similarly, Lopez-Molina et al. (2013) proposed a multiscale method that used a combination of Gaussian filter, Sobel operators, and a new edge tracking procedure that followed a coarse-to-fine approach to get the desired edges. Kiani and Sahebi (2015) developed an algorithm that employed piecewise thresholding and Shannon entropy, in that the threshold of various image regions was computed using a piecewise process. Next, the suitable thresholds were extracted by a specialized process. Lastly, the regions' borders were obtained by utilizing Shannon entropy. Liu and Fang (2015) followed a different methodology as it included the use of an ant colony optimization (ACO) concept. In this method, the ACO concept was utilized with a novel heuristic function, an adapted thresholding process, and a specialized updating procedure to produce the desirable edges. Zhang et al. (2017) applied an advanced approach by using Gaussian anisotropic kernels (GAK). This method operated by smoothing the input image by GAK. Then, a directional anisotropic derivative filter was computed with edge gradient direction and edge strength maps. Next, the gradient direction and magnitude were calculated for each pixel, followed by a hysteresis thresholding process to acquire the desired edges. Ansari et al. (2018) developed an algorithm that used information theory and fuzzy concepts, whereby it began by dividing the input image into different blocks. Next, the divergence measure and its minimum value were determined to filter all the blocks. After that, all the blocks were filtered using the maximum divergence measure. Then, the maximum values were considered and limited to produce the edge detected image. Wang et al. (2019) utilized a different tactic by applying the convolutional neural network approach. This method worked by using the ResNet101 network through combining the created blocks in various compositions and downsampling them to get the characteristic maps. Next, these maps were fused in different situations to obtain the outcome. Liu et al. (2020) developed a statistical-based method for edge detection. This method used 2D entropy to simplify a given image into three groups, whereby each group had a reference number that was determined using statistics of edge proportions. Using these numbers and edge directions, important points were obtained if they owned a high probability of edges. Then, the obtained points were joined to form the detected edges. Finally, El-Sayed et al. (2020) proposed a two-step procedure to detect the edge. It started by inputting the image, and then computing its average, probability, and optimal threshold. Next, the optimal threshold was sent to the second procedure along with the original image to compute a binary image, and then filter it by a specialized 3×3 mask. Next, the threshold was utilized along with some filtration rules and entropies to produce the detected edge. Katırcıoğlu (2020) introduced a heat conduction matrix (HCM) based method, in that the HC equation was initially utilized and the matrix of characteristics was acquired. The second phase included limiting the previously obtained matrix to obtain the outcome.

As noticed from the reviewed methods, the standard methods can rapidly detect the edges. Still, not many edges are noticed in the results. On the other hand, the advanced methods utilize complex computations to better detect edges. Nevertheless, the computational cost of such methods is high, as they utilize numerous steps, involving iterative calculations, and may include artificial intelligence techniques to compute some optimal solutions. Moreover, several methods require numerous inputs, making them difficult to tune and be used in real-life applications. Therefore, developing an algorithm that requires few computations, is fully automatic, and can provide a high edge detection is desirable, and such an issue is still open for research and development.

METHODOLOGY

As mentioned earlier, edge detection is an essential phase in numerous imaging-related procedures. Moreover, the concept of entropy has been increasingly used in the past decades as an information measure that can be employed to characterize image texture (Gray, 2011). Besides, developing a fully automatic method with a low computation cost is highly required. Keeping all that in mind, the multi-phase information theory (MPIT) based algorithm was developed to address these issues. The proposed method operated by segmenting the input image via three optimal thresholding values that were determined using Shannon and generalized Hill entropies. Then, specific rules were applied, and the output was passed to an edge detection approach to extract the solid edges and deliver the outcome. In detail, Shannon entropy is deemed an essential subject in information theory due to its usefulness in measuring the amount of information held in data. Suppose that X is a variable that is discrete and arbitrary with potential results as $x_1, \ldots, x_n$ and probability as $P(x_1), \ldots, P(x_n)$, its entropy can be described by Shannon as in Equation 1 and its extensive property can be defined as in Equation 2 (Shannon, 1948):

$$S(X) = -\sum_{i=1}^{n} P(x_i) \cdot \log P(x_i) \tag{1}$$

$$S(X+Y) = H(X) + H(Y) \tag{2}$$

Next, the following Equation 3 is utilized to compute the optimum threshold value as:

$$t_S^{opt} = \arg\max\left[S(X) + S(Y)\right] \tag{3}$$

On the other hand, the Hill entropy is a generalized one-parameter version of Shannon entropy. It can be computed as in Equation 4 (Singh & Singh, 2008):

$$H_\alpha = \left(\sum_{i=1}^{n} p_i^\alpha\right)^{\left(\frac{1}{1-\alpha}\right)} \tag{4}$$

where, parameter α has a positive real other than 1, and in this work, its value was set to 0.5. The Hill entropy can be reduced to Shannon entropy once the value of α approaches 1. Moreover, it is deemed a non-extensive type of entropy (Hill, 1973). Therefore, its total satisfies the pseudo-additive rule when the system H_a becomes composed of two independent subsystems X and Y as in Equation 5:

$$H_a(X+Y) = H_a(X) + H_a(Y) + (1-a)\cdot H_a(X)\cdot H_a(Y) \tag{5}$$

Furthermore, the probability distribution of object and background for a given image with n as gray-levels and t as threshold can be determined as in Equations 6 and 7 (Hill, 1973):

$$p_X : \frac{p_1}{p_X}, \frac{p_2}{p_X}, \ldots, \frac{p_t}{p_X}, \quad p_Y : \frac{p_{t+1}}{p_Y}, \frac{p_{t+2}}{p_Y}, \ldots, \frac{p_n}{p_Y} \tag{6}$$

$$P_X = \sum_{i=1}^{t} p_i \; , \quad P_Y = \sum_{i=t+1}^{n} p_i \tag{7}$$

Besides, the Hill entropy of object (H^X) and background (H^Y) can be defined as in Equation 8, while the optimum threshold parameter that maximizes the function is determined as in Equation 9 (Elaraby & Moratal, 2017):

$$H_\alpha^X = \sum_{i=1}^{w}\left(\frac{p_i^\alpha}{P_X}\right)^{\frac{1}{1-\alpha}} , \quad H_\alpha^Y = \sum_{i=1}^{w}\left(\frac{p_i^\alpha}{P_Y}\right)^{\frac{1}{1-\alpha}} \tag{8}$$

$$t_H^{opt} = \arg\max\left[H_\alpha^X(t) + H_\alpha^Y(t) + (1-\alpha)\cdot H_\alpha^X(t)\cdot H_\alpha^Y(t)\right] \tag{9}$$

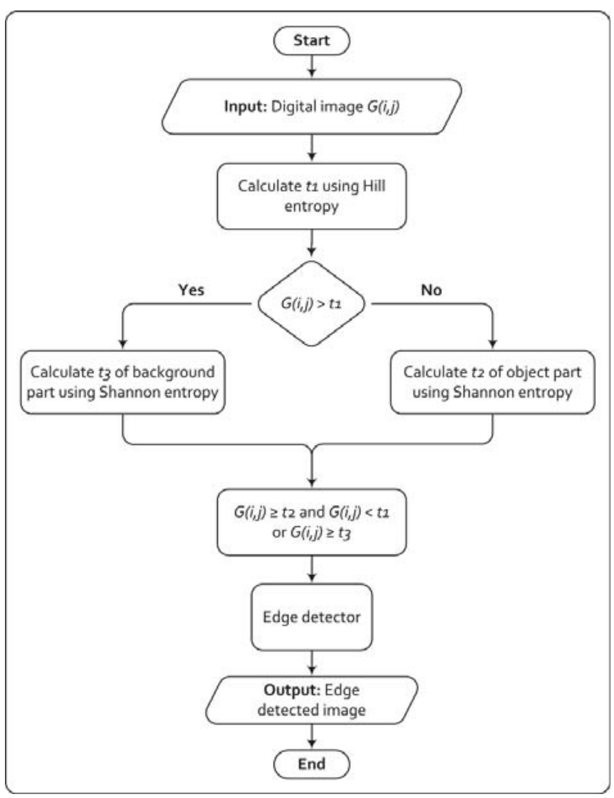
As for the edge detector, it can be explained as follows: Let $m = 2a + 1$, $n = 2b + 1$, where a and b are non-negative integers, and the matrix w that has the size of $m \times n$ is a spatial filter mask, in that 3×3 is the smallest meaningful size. When moving the mask window across the entire image, the probability of each in-center pixel in the mask is determined by entropy, in that when it equals 1 or is lower than the value of the in-center pixel, it is not deemed an edge material. If the other situations occur, the in-center pixel is deemed an edge material (Elaraby & Moratal, 2017). To clarify the working mechanism of the proposed method, the steps can be described in brief as the following:

- **Phase 1:** Determine the global threshold parameter (t_1) by utilizing Hill entropy.
- **Phase 2:** Determine the local threshold parameters (t_2) and (t_3) by utilizing Shannon entropy.
- **Phase 3:** Apply the filtration rules.
- **Phase 4:** Implement the edge detector.

Finally, the schematic workflow of the proposed automatic edge detection algorithm is given in Figure 1, where t_1 is calculated by Shannon entropy (Shannon, 1948), while t_2, and t_3 are calculated by Hill entropy (Hill, 1973).

Figure 1

Schematic Workflow of the Introduced Algorithm



RESULTS AND ANALYSIS

This section is organized as follows: first, the material associated with the employed dataset is mentioned. Then, the comparison algorithms are identified and the evaluation methods for the obtained outputs are explained. Next, the computer specifications and the programming environment are stated, followed by the identification of the upcoming figures and tables. Afterward, the experimental results are demonstrated and explained, followed by the attained comparisons' outcomes and their related discussions. Finally, some concluding remarks are provided. As for the dataset of images, two of such were employed in this study. The first was a dataset of more than one hundred images of different sizes, which were gathered from several online repositories. The images were cropped, and their sizes were unified to become 512×512. Some of these images were color images and they were converted to grayscale. These images were collected from websites such as unsplash.com, sciencephoto.com, gettyimages.com, shutterstock.com, stocksnap.io, and skitterphoto.com. From this dataset, 100 images were used for experiments and comparisons. The second was the VEDAI dataset (Razakarivony & Jurie, 2016), which included more than one thousand and two hundred 512×512 color aerial images of different views. From this dataset, 500 images were used for experiments and comparisons. Figure 2 shows some image samples of the utilized datasets arranged as a gallery.

As for the comparison methods, six of such were used, i.e., Roberts, Prewitt, Sobel (Abdou & Pratt, 1979), Laplacian 8-Neighborhood (L8N) (Berzins, 1984), Canny (Canny, 1986), and LoG (Masoud & Bayoumi, 1995). The working mechanism of the comparison methods has already been explained in the related work section of this study. As for the used evaluation metrics, three of such wee utilized, namely edge intensity (EI) (Wang et al., 2012), mean gradient (MG) (Bai & Zhang, 2014), and spatial frequency (SF) (Yang et al., 2020). The EI metric quantifies the overall quantity of the edges by computing their density depending on the available intensities of the detected edges. It simply shows how much edge information is included in an image, by indicating whether the evaluated image is rich with edge information. The EI metric is computed as in Equation 10:

$$EI = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} E_{(i,j)}}{M \cdot N} \tag{10}$$

where, $E_{(i,j)}$ is an image that has the detected edge information, M and N are the dimensions of $E_{(I,j)}$, (i, j) are the image coordinates, and $(\cdot)$ is a multiplication process.

Figure 2

Gallery of Some Image Samples Related to the Utilized Datasets

The MG metric quantifies the quality based on the detected gradients, which indicate the availability and clarity of visual information. It can be a helpful method in showing the strength of the detected edge information. The MG metric can be computed as in Equation 11:

$$MG = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} G_{(i,j)}}{M \cdot N} \tag{11}$$

where, $G_{(i,j)}$ is an image that has the gradient information of the edge-detected image.

The SF metric quantifies the availability of clear information in an image, in that it can help to show the clarity, richness, and information perceptiveness of the detected edges. The SF metric can be computed as in Equation 12:

$$SF = \sqrt{(F_R)^2 + (F_C)^2} \tag{12}$$

where, F_R is the row frequency and F_C is the column frequency, whereby they can be computed as in Equations 13 and 14, respectively:

$$F_R = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(E_{(i,j)} - E_{(i-1,j)}\right)^2}{M \cdot N} \tag{13}$$

$$F_C = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(E_{(i,j)} - E_{(i,j-1)}\right)^2}{M \cdot N} \tag{14}$$

In brief, EI signified edge quantity, MG indicated edge strength, and SF denoted edge clarity. The output of the three used methods is simply a number that is larger than 0, wherein a greater number suggests better results and vice versa. To measure the complexity of the comparison methods, the processor runtime was recorded for each method, which was all run under the same programming environment. The programing environment used to develop the proposed algorithm and run the experiments and comparisons was MATLAB 2019a. The laptop utilized in this study had an Intel Core i7-6700K processor and 16 gigabytes of memory. Figure 3 to Figure 6 demonstrate the experimental attained outcomes by the proposed algorithm for different experiments. Figure 7 to Figure 9 show the attained results of different companions. Table 1 provides the achieved evaluation scores for the comparison methods. Figures 10 and 11 illustrate the graphs of the mean evaluation records in Table 1.

Figure 3

Detecting the Edge of Different Aerial Images Using the Proposed Algorithm (VEDAI Dataset Batch 1). (a1-a5) aerial images; (b1-b5) the detected edges of images (a1-a5)

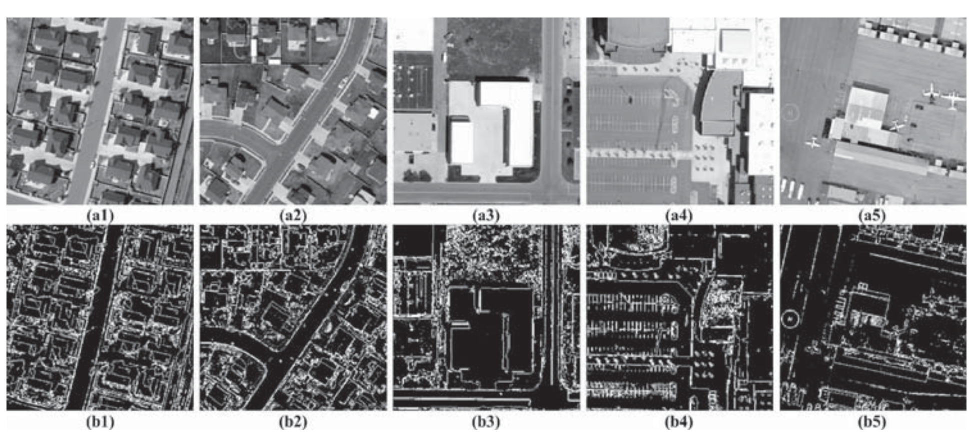


Figure 4

Detecting the Edge of Different Aerial Images Using the Proposed Algorithm (VEDAI Dataset Batch 2). (a1-a5) aerial images; (b1-b5) the detected edges of images (a1-a5)

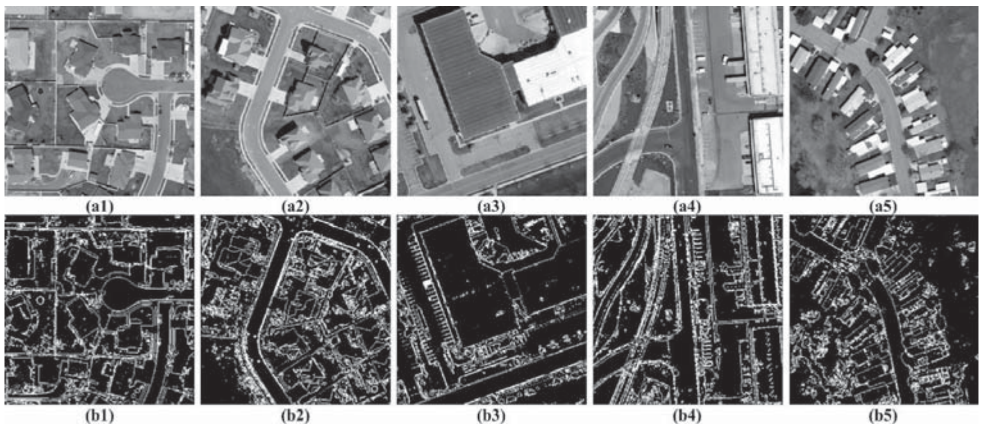


Figure 5

Detecting the Edge of Different Aerial Images Using the Proposed Algorithm (Internet Dataset Batch 1). (a1-a5) aerial images; (b1-b5) the detected edges of images (a1-a5)

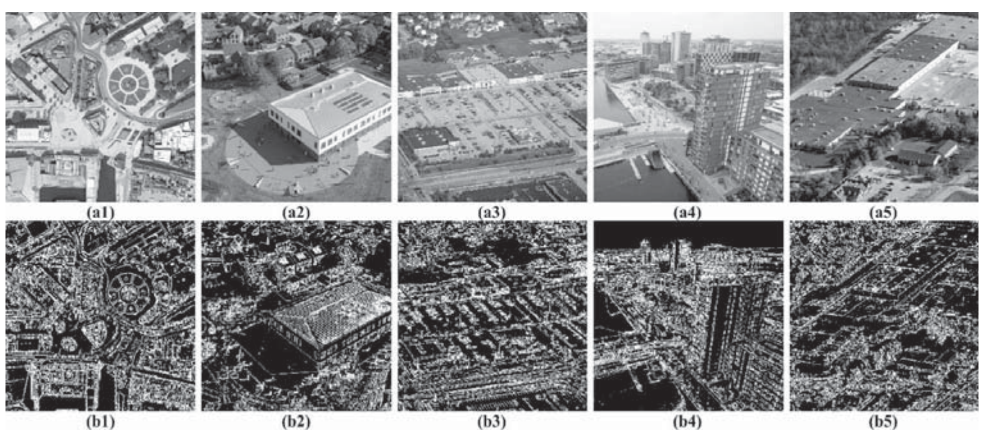
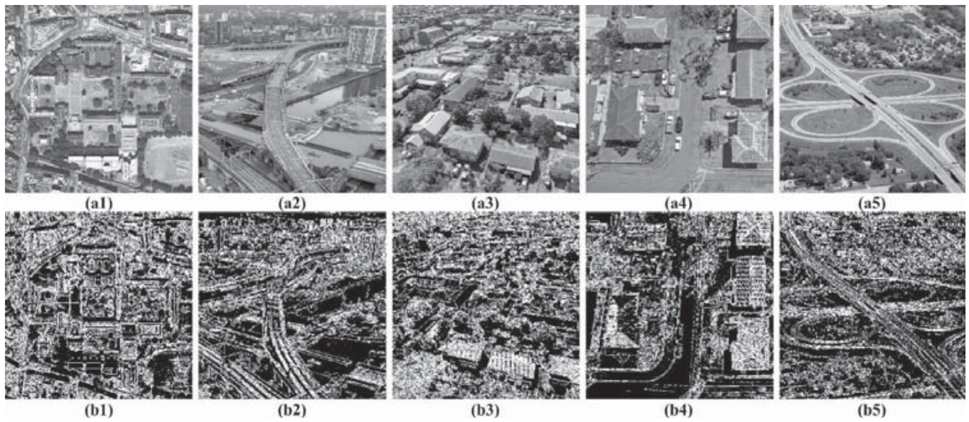


Figure 6

Detecting the Edge of Different Aerial Images Using the Proposed Algorithm (Internet Dataset Batch 2). (a1-a5) aerial images; (b1-b5) the detected edges of images (a1-a5)



The experimental results in Figure 3 to Figure 6 revealed the filtering abilities of the developed algorithm with dissimilar aerial images. The resulting images had solid edges with strong intensities. Moreover, the outcomes demonstrated that the developed algorithm had tremendous abilities in detecting the edge information in which most of the edge information was displayed without significant discontinuities. Besides, no noisy details were noticed in the results. Likewise, the detected edges had a realistic and rich appearance. Such results were obtained due to the utilization of a well-structured algorithm that employed two robust types of entropies, i.e., Shannon and Hill, and specialized filtration rules with a non-complex edge indicator to identify the important image edge details. This was an important achievement because such promising results were obtained with an algorithm that did not require many calculations yet produced satisfactory results.

From the comparison outcomes in Figure 7 to Figure 11 and Table 1, it was observed that each comparison method resulted in different outcomes because each approach used a different methodology. For the Roberts method (Abdou & Pratt, 1979), it only detected a few edges with many discontinuities. For this reason, it scored very low in EI and MG, low in SF, and was the fifth fastest method according to the processor runtime. Prewitt and Sobel (Abdou & Pratt, 1979) were almost similar with a slight favor to Prewitt as indicated by EI, MG, and SF. Prewitt scored low in MG and EI, below moderate in SF, and was the second fastest method according to the processor runtime. Sobel scored below moderate in MG and EI, moderate in SF, and was the fastest method according to the processor runtime. By observing the output images of these methods, they seemed almost identical, in that the detected edges were not that many and only the highly significant edges were identified.

The LoG method (Masoud & Bayoumi, 1995) discovered more edges than the aforesaid methods with slightly dimmed intensity. It scored above moderate in EI, MG, and SF, and was the fourth fastest method according to the processor runtime. Lower quality results were obtained by the L8N method (Berzins, 1984) in terms of EI and MG as it provided less edge quantity and strength, scoring moderately with these metrics. Still, it performed the worst according to the SF metric as this method discovered many noises along with the edge information, making its outcomes not as clear as the other comparison methods, and was the third fastest method according to the processor runtime. The Canny method (Canny, 1986) performed well in all the used metrics as it provided high performances due to the produced edge quantity, strength, and clarity. Even so, it was the seventh fastest method according to the processor runtime.

Figure 7

The Comparison Outcomes (First Comparison). (a) Original image; the edge of the other images is detected by: (b) Roberts; (c) Canny; (d) Prewitt; (e) Sobel; (f) LoG; (g) L8N; (h) VAACO; (i) HCM; (j) Proposed algorithm

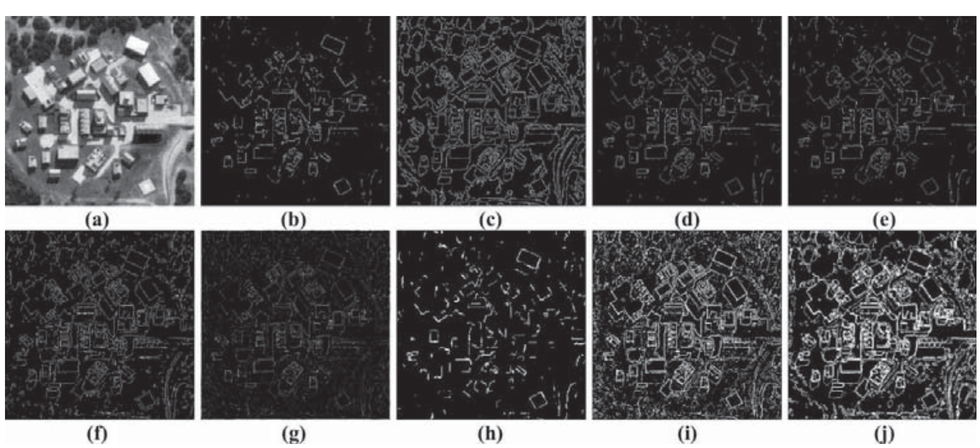


Figure 8

The Comparison Outcomes (Second Comparison). (a) Original image; the edge of the other images is detected by: (b) Roberts; (c) Canny; (d) Prewitt; (e) Sobel; (f) LoG; (g) L8N; (h) VAACO; (i) HCM; (j) Proposed algorithm

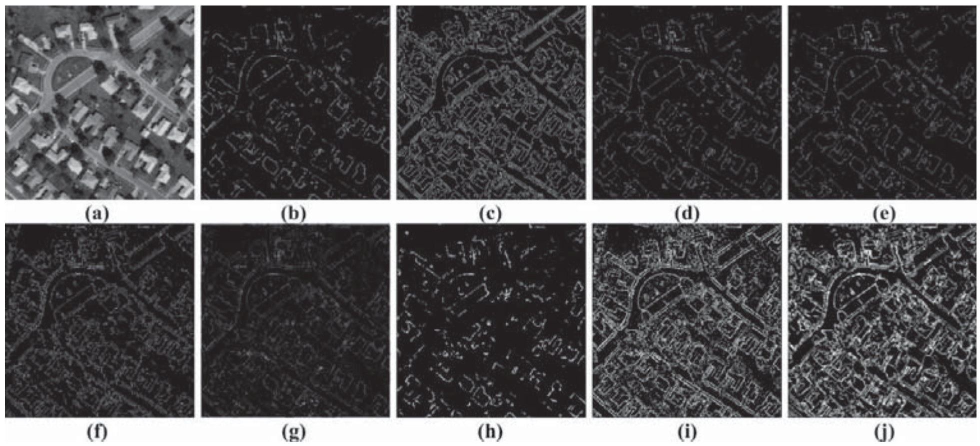
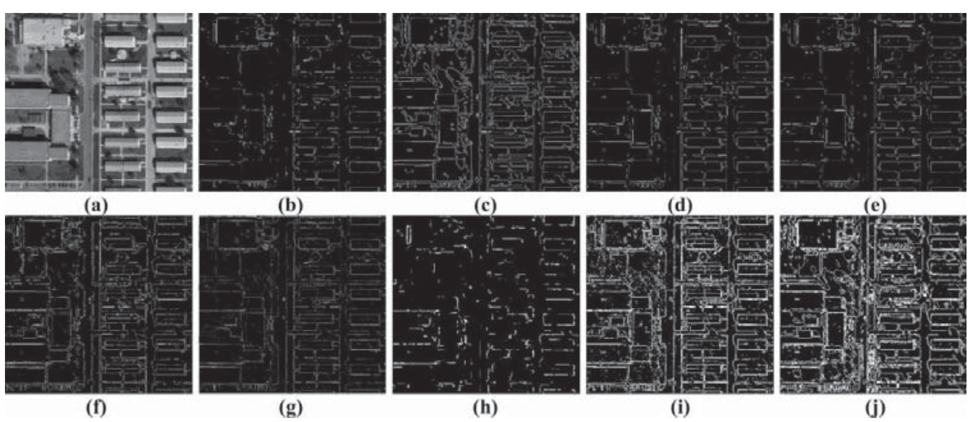


Figure 9

The Comparison Outcomes (Third Comparison). (a) Original image; the edge of the other images is detected by: (b) Roberts; (c) Canny; (d) Prewitt; (e) Sobel; (f) LoG; (g) L8N; (h) VAACO; (i) HCM; (j) Proposed algorithm



The VAACO method (Tian et al., 2011) detected low edge ratios with many gaps. For this reason, it scored the worst in EI and MG, very low in SF, and was the slowest method according to the processor runtime. The HCM method (Katırcıoğlu, 2020) worked very well and detected numerous edge information, and it was very competitive to the proposed method. It scored the second best in terms of EI, MG, and SF, yet was somewhat slow as it was the eighth fastest method according to the processor runtime. The best performance went to the proposed method as it recorded the best in terms of the used edge evaluation methods. Moreover, its results were well-observed, had a high edge discovery with strong intensities, clear details, and it discovered the most edges among the comparison methods. This was a true achievement as such a low-complexity algorithm (scoring the sixth fastest method according to the processor runtime) showed rewarding outcomes. Designing a high dependability algorithm for edge detection is difficult as many challenges exist in this domain. Nevertheless, such a task was accomplished as demonstrated by the outcomes of the proposed algorithm and according to the image evolution metrics. The proposed algorithm can be utilized in different image processing and computer vision systems that require a simple yet efficient method to achieve the edge detection task. For future research, this algorithm can be further modified by utilizing other processing concepts to further increase its precision in detecting the important edges of images.

Table 1

The Attained Evaluations for the Comparison Methods

Methods	ID	EI	MG	SF	Runtimes
Roberts (Abdou & Pratt, 1979)	Fig. 7	9.0712	11.5419	67.9437	0.07288
	Fig. 8	9.6663	13.1	71.0686	0.076823
	Fig. 9	10.7785	12.4542	73.346	0.075142
	Avg	9.8386	12.3653	70.7861	0.07494
Canny (Canny, 1986)	Fig. 7	29.0878	36.9627	121.6758	0.127332
	Fig. 8	31.068	40.892	125.4692	0.147228
	Fig. 9	25.3393	29.3161	112.7838	0.125329
	Avg	28.4983	35.7236	119.9762	0.13329
Prewitt (Abdou & Pratt, 1979)	Fig. 7	10.5164	14.0975	78.8997	0.005186
	Fig. 8	10.3809	14.8928	82.2375	0.009082
	Fig. 9	12.8669	14.811	82.3568	0.006034
	Avg	11.2547	14.6004	81.1646	0.00676
Sobel (Abdou & Pratt, 1979)	Fig. 7	10.5556	14.2426	79.4738	0.004255
	Fig. 8	10.4403	15.0347	83.0766	0.005893
	Fig. 9	12.898	14.9369	82.7512	0.005373
	Avg	11.2979	14.738	81.7672	**0.00517**
LoG (Masoud & Bayoumi, 1995)	Fig. 7	19.9769	27.5929	110.3958	0.055309
	Fig. 8	19.6886	28.3486	114.6528	0.071517
	Fig. 9	21.3169	26.1776	108.5508	0.066696
	Avg	20.3274	27.373	111.1998	0.0645

(continued)

Methods	ID	EI	MG	SF	Runtimes
L8N (Berzins, 1984)	Fig. 7	20.6604	21.4302	44.9135	0.039508
	Fig. 8	20.9087	22.527	48.0349	0.042557
	Fig. 9	23.5748	23.6888	54.5555	0.039966
	Avg	21.7146	22.5486	49.1679	0.0406
VAACO (Tian et al., 2011)	Fig. 7	10.0188	10.5286	59.493	72.0850
	Fig. 8	8.3942	9.2614	56.8139	273.7505
	Fig. 9	8.9377	9.5036	57.076	159.0955
	Avg	9.1169	9.7645	57.7943	168.3103
HCM (Katırcıoğlu, 2020)	Fig. 7	42.2553	49.9004	134.8281	3.772901
	Fig. 8	41.8141	49.7622	132.8934	6.32672
	Fig. 9	41.3793	43.7836	121.2636	5.364782
	Avg	41.8162	47.8154	129.6617	5.1548
Proposed MPIT	Fig. 7	54.464	49.0868	131.1794	0.101854
	Fig. 8	51.7832	50.1684	134.025	0.11214
	Fig. 9	54.1329	46.9786	124.8977	0.096345
	Avg	**53.46**	**48.7446**	**130.034**	0.1034

Figure 10

Graphical Form of the Average EI and MG

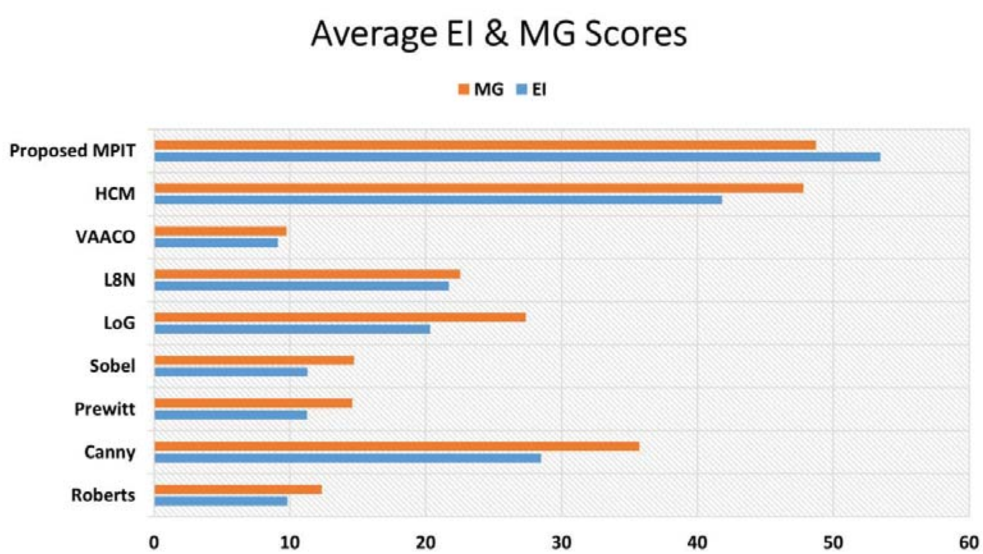
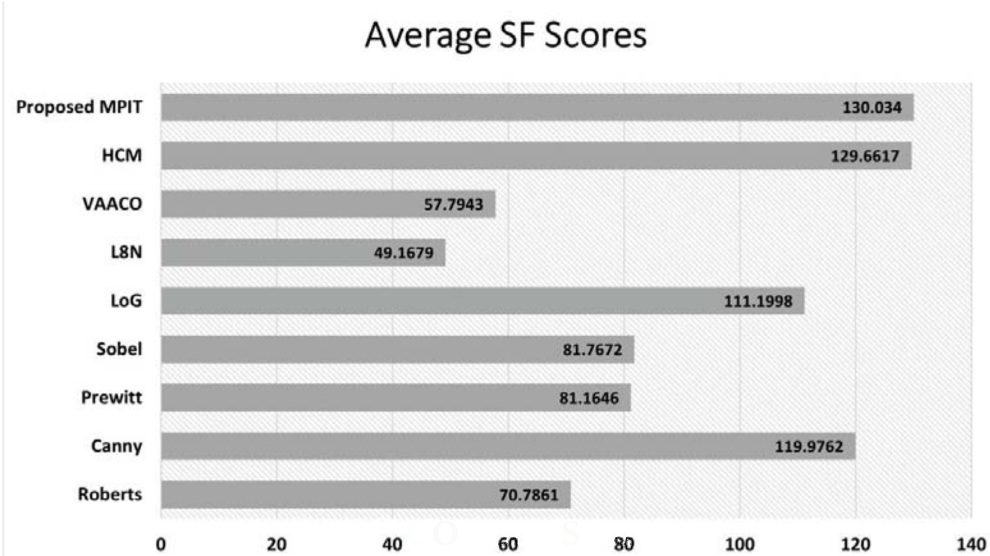


Figure 11

Graphical Form of the Average SF



In this study, a multi-phase information theory-based algorithm was developed for edge detection. The proposed algorithm utilized a combination of Shannon and Hill entropies with specific rules along with a non-complex edge detector to achieve its task. It also depended on the following criteria to produce adequate results: density, intensity, roughness, and region size. The reliability of the methodology was cross-checked with expert evaluations of edge detection results. The experimental results were explained by subjective evaluations, whereas the comparison results were clarified by subjective and objective evaluations. The results revealed the preeminence of the proposed algorithm as it produced well-structured edges and was able to detect most of the important image edges and displayed them clearly with rich intensities. Moreover, it scored the best in the used image evaluation metrics. Such findings were vital because the results were obtained by a low-intricacy and fully automatic algorithm. For future research, some additional developments may be applied to improve the detection of edges of images that are captured by other imaging modalities.

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