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An improved teaching–learning based robust edge detection algorithm for noisy images

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GRAPHICAL ABSTRACT

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ABSTRACT

This paper presents an improved Teaching Learning Based Optimization (TLO) and a methodology for obtaining the edge maps of the noisy real life digital images. TLO is a population based algorithm that simulates the teaching–learning mechanism in class rooms, comprising two phases of teaching and learning. The 'Teaching Phase' represents learning from the teacher and 'Learning Phase' indicates learning by the interaction between learners. This paper introduces a third phase denoted by “Avoiding Phase” that helps to keep the learners away from the worst students with a view of exploring the problem space more effectively and escaping from the sub-optimal solutions. The improved TLO (ITLO) explores the solution space and provides the global best solution. The edge detection problem is formulated as an optimization

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Introduction

Edge Detection (ED) that provides continuous contours of the object boundaries is low-level feature detection in image analysis and computer vision such as shape recognition, 3D reconstruction and defect detection on mechanical parts. Precise information about edges is vital to the success of such systems. Edges are sets of pixels in the image regions with sharp intensity changes and correspond to visible contour features of objects in an image. Normally, ED is a process that inputs a grey scale image and then results in a binary edge map to indicate the edges of objects [1,2]. The shape of edges depends on many parameters, such as geometrical and optical properties of an image, illumination conditions and noise level in the image [3].

Several ED theories and algorithms have been suggested in the recent decades [1]. They can be grouped into two categories, Gradient and Laplacian operators [1]. There are other ED methods such as snake methods [4] and mathematical morphology [5]. Methods based on Gradient operators mainly include the Roberts operator [6], the Prewitt operator [7] and the Sobel operator [8]. Methods based on Laplacian operators mainly include Laplacian of Gaussian Method [9] and Canny edge detector [10]. Both gradient-based and Laplacian based ED methods have some disadvantages such as noise sensitivity, illumination sensitivity and non-adaptive parameters [1]. Some new approaches that include a multi-scale method for ED based on increasing Gaussian smoothing and edge tracking [11] and a model based on the multi-scale and multi-expert analyses inspired by common vector approach and the concept of Gaussian scale [12] have been outlined. An objective performance analysis of statistical tests for ED of textured or cluttered images has been performed [13].

Most of the existing algorithms are based on first and second derivatives, Gaussian filters, statistics, soft computing techniques and different transforms. They employ a thresholding technique to classify a pixel as an edge or non-edge based on its magnitude, a pixel with a weak magnitude may be recognized as non-edge and accordingly the edges become broken. Noise phenomena is an important hindrance to the detection of continuous edges [14]. It causes some variation of pixel intensities and accordingly reduces the performance of an ED algorithm in noisy images. Another vital barrier that complicates the operation of ED is illumination phenomena that cause the magnitude of the edges in the illuminated areas to become weak [15]. Though most of the classical ED algorithms are computationally efficient and perform well while the image has good quality and the object contours are distinct, they are susceptible to noise and suffer from producing broken edges. Besides, these algorithms often may not effectively detect the object boundaries for complex objects with noise or with complex texture such as medical images, which are often vague, especially for skin lesions.

Evolutionary algorithms such as harmony search optimization [16], ant colony optimization (ACO) [17], cuckoo search optimization [18] and particle swarm optimization [19] have been applied for ED with a view of overcoming the drawbacks of classical approaches. More recently Teaching–Learning-Based Optimization (TLO) has been suggested from the inspiration of teaching–learning mechanism in class rooms by Rao et al. [20,21] and Rao and Patel [22] for solving complex optimization problems, and applied for real world optimization problems such as parameter optimization of modern machining processes [23], optimal power flow [24] and unit commitment [25], to date, it has not been applied to ED.

The focus of this article was to develop an improved TLO (ITLO) algorithm for ED of digital noisy images with a view of effectively obtaining continuous and thin edges besides reducing broken and jagged edges. The results of the developed algorithm are compared with those of the ACO, Sobel and Canny edgy detection algorithms with a view of exhibiting the superiority of the algorithm.

Methodology

Improved TLO

TLO is developed from the inspiration of teaching–learning mechanism in class rooms for solving optimization problems and involves two crucial mechanisms, represented as teaching and learning phases.

Teaching phase

The teaching phase denotes the global search process of the TLO. The knowledgeable teacher attempts to enhance the performance of the learners through teaching. He aims to improve the mean grade point of each subject of all the learners to his

Fig. 1 (a) Eight movement direction, (b) representation of an Edge Segment centred around a pixel, (c) encoding.
The change in the grade point of the \( j \)-th subject at \( k \)-th iteration, \( \Delta G^j_k \), is expressed as

\[
\Delta G^j_k = \text{rand}(0, 1) \times (G^j_k \text{teacher} - t_f \times G^j_k \text{ave})
\]  

(1)

where 
\( G^j_k \text{teacher} \) indicates grade of the \( j \)-th subject of the teacher at \( k \)-th iteration
\( G^j_k \text{ave} \) represents the mean grade of the \( j \)-th subject at \( k \)-th iteration and is computed by

\[
G^j_k \text{ave} = \frac{1}{nS} \sum_{i=1}^{nS} G^j_k
\]  

(2)

\( nS \) indicates the number of students 
\( t_f \) denotes the teaching factor and is computed by

\[
t_f = \text{round}([1 + \text{rand}(0, 1)] \{1, 2\})
\]  

(3)

The grades of each learner is updated by

\[
G^{j+1}_k = G^j_k + \Delta G^j_k
\]  

(4)

Learning phase

The learning phase represents the local search mechanism of TLO. Each learner in the class room attempts to enhance his performance by acquiring knowledge through interaction with other learners. The grades of \( p \)-th learner after interaction with \( q \)-th learner are updated by the following:

\[
G^{p+1}_k = \begin{cases} 
G^p_k + \text{rand} \times (G^p_k - G^q_k) & \text{if } F_p > F_q \\
G^p_k + \text{rand} \times (G^q_k - G^p_k) & \text{if } F_p < F_q
\end{cases}
\]  

(5)

where \( F_p \) is the performance measure of the \( p \)-th learner.

Avoiding phase

The interactions in the learning phase may lead to inappropriate knowledge exchange between learners in such a way that the solution can be trapped at local minima. Another phase, represented as avoiding phase, is required to come out from the sub-optimal traps in addition to searching unexplored regions in the solution space. This phase is inspired from the fact that the learners in general intend to move with the teacher for learning and avoid the worst students with a view of keeping themselves away from the mischief activities of the worst students. The behaviour of learners in respect of worst students helps to explore the problem space more effectively and escape from the sub-optimal solutions. The behaviour of the worst student can be modelled by

\[
G^0_{\text{worst}}(k) = G_{\text{worst}}(k) + q \times \frac{1}{1 + k/K_{\text{max}}} 
\]  

(6)

where
\( G_{\text{worst}}(k) \) denotes grade points of the worst student at \( k \)-th iteration
\( G^0_{\text{worst}}(k) \) represents the modified grade points of the worst student at \( k \)-th iteration
\( K_{\text{max}} \) is the maximum number of iterations

The grade points of the learner as a result of avoiding the worst student can be modeled by the following equations

\[
G^{p+1}_k = \begin{cases} 
G^p_k + \rho \times \text{ed} & \text{if } \text{ed} > 0 \\
G^p_k - \rho \times \text{ed} & \text{if } \text{ed} < 0
\end{cases}
\]  

(7)

where \( \text{ed} \) is the Euclidean distance between worst student and the learner and \( \rho \) represents the avoiding rate.

Eq. (7) permits the learners to avoid the worst student, thereby escaping from sub-optimal solution traps in the search space and improving the capability of exploration. It forces the population to arrive at the global best solution.

Proposed method

Many of the existing ED algorithms convolve a convolution matrix on an image to calculate the edge magnitude only for a single pixel at a time and then classify it as an edge or a non-edge by comparing with a thresholding technique,
| Test Image | Proposed Method | ACO [17] | Canny [10] | Sobel [8] |
|------------|-----------------|----------|------------|----------|
| ![Image](test_image_1.png) | ![Proposed Method](proposed_method_1.png) | ![ACO](aco_1.png) | ![Canny](canny_1.png) | ![Sobel](sobel_1.png) |
| ![Image](test_image_2.png) | ![Proposed Method](proposed_method_2.png) | ![ACO](aco_2.png) | ![Canny](canny_2.png) | ![Sobel](sobel_2.png) |
| ![Image](test_image_3.png) | ![Proposed Method](proposed_method_3.png) | ![ACO](aco_3.png) | ![Canny](canny_3.png) | ![Sobel](sobel_3.png) |
| ![Image](test_image_4.png) | ![Proposed Method](proposed_method_4.png) | ![ACO](aco_4.png) | ![Canny](canny_4.png) | ![Sobel](sobel_4.png) |

(a) Without any noise

| Test Image | Proposed Method | ACO [17] | Canny [10] | Sobel [8] |
|------------|-----------------|----------|------------|----------|
| ![Image](test_image_1.png) | ![Proposed Method](proposed_method_1.png) | ![ACO](aco_1.png) | ![Canny](canny_1.png) | ![Sobel](sobel_1.png) |
| ![Image](test_image_2.png) | ![Proposed Method](proposed_method_2.png) | ![ACO](aco_2.png) | ![Canny](canny_2.png) | ![Sobel](sobel_2.png) |
| ![Image](test_image_3.png) | ![Proposed Method](proposed_method_3.png) | ![ACO](aco_3.png) | ![Canny](canny_3.png) | ![Sobel](sobel_3.png) |
| ![Image](test_image_4.png) | ![Proposed Method](proposed_method_4.png) | ![ACO](aco_4.png) | ![Canny](canny_4.png) | ![Sobel](sobel_4.png) |

(b) With Gaussian noise

**Fig. 3** Results of real life images. (a) Without any noise; (b) with Gaussian noise; and (c) with Impulse noise.
thereby falsely classifying the pixels with weak magnitudes as non-edges and a few noisy pixels with high magnitude as edges. It may cause discontinuous edges or some speckles to appear on a resulting edge map. The proposed method attempts to search the best possible segment of a given length of edge with a view of correcting the discontinues caused due to the presence of noises and illumination. The proposed method involves representation of decision variables associated with an edge segment and formation of a performance function.

**Representation of control variables**

The connectivity between a chosen pixel and its neighbouring pixel of an edge can be denoted by an angle that varies in the range of \((0–360^\circ)\) in steps of \(45^\circ\), as marked in Fig. 1(a). An example edge segment, centred around a chosen pixel \(P\), is represented by a set of angles that represent directions to the next pixel and are encoded as indicated in Fig. 1(b) and (c) respectively. The grade points of \(i\)-th learner \(G_i\) in the proposed method are tailored to denote the control variables associated with an edge segment for a chosen pixel \(P\) as follows:

\[
G_i = \begin{bmatrix} \theta_1 & \theta_2 & \cdots & \theta_N \\ \theta_{-1} & \theta_{-2} & \cdots & \theta_{-N} \end{bmatrix}
\]

(8)

where \(\theta_j\) represents angle direction of the previous pixel \((P_{j-1})\) to \(j\)-th pixel \((P_j)\) of the edge segment.

In this representation, the first row and second row of entries indicate the first and second half of the edge segment, starting from the chosen pixel \(P\) respectively.

**Performance function**

The ITLO algorithm searches for global best solution by maximizing a performance function \(F\), which is to be formulated for each of a chosen pixel \(P\). In the light of the fact that an edge is a set of continuous pixels that result in two regions: the light and dark regions, as indicated in Fig. 1 (b), the proposed method processes a set of pixels at a time instead of a single pixel with a view to extract the real edge. The set of consecutive pixels is identified as an edge, when they maximize the interset distance between the pixel intensities of the two regions and minimize the intraset distances within the regions. The edge magnitude of a chosen pixel \(P\) in a movement direction \(m\) in terms of interest and intraset distances can be formulated as a maximization function [19] as
\[ E_{P,m} = \frac{\min \left( 1, \frac{A_{P,m}^{\text{light}} - A_{P,m}^{\text{dark}}}{w_1} \right)}{1 + \left( \sum_{n \neq m} \min \left( \frac{1}{2N}, \frac{1}{2N} \right) \right) + \sum_{n \neq m} \min \left( \frac{1}{2N}, \frac{1}{2N} \right)} \]

where
\[ E_{P,m} \text{ indicates edge magnitude of } P \text{ in a movement direction } m \]
\[ A_{P,m}^{\text{light}} \text{ and } A_{P,m}^{\text{dark}} \text{ denote average intensity of the dark and light regions in movement direction } m \text{ for pixel } P \text{ respectively} \]
\[ I_P \text{ represents intensity of the neighbouring pixel } P_i \]
\[ \text{dark and light indicate dark and light regions around the chosen pixel } P \]
\[ N \text{ denotes total number of pixels in each half of the edge segment around the chosen pixel } P \]

The edge magnitude of a chosen pixel \( P \) in a movement direction \( m \) can be thinned [26] by employing the criterion of non-maxima suppression
\[ E_{P,m}^{\text{thin}} = E_{P,m} \cdot e^{-2(\beta_{P,m} - 4)} \]

where
\[ \beta_{P,m} \text{ indicates non-maxima suppression factor of pixel } P \text{ in a movement direction } m \text{ and is evaluated by} \]
\[ \beta_{P,m} = P_{\text{loc}}[1,2,3,4,5,6]; \quad E_{P,m} < E_{P,m} \]
\[ E_{P,m}^{\text{thin}} \text{ represents thinned edge magnitude of } P \text{ in a movement direction } m \]
\[ E_{P,m} \text{ indicates edge magnitude of } P \text{ in a movement direction } m \]

The probability of pixel \( P \) lying on an edge in a movement direction \( m \) can be represented by a sigmoid function as
\[ \Theta_{P,m} = \frac{1}{1 + e^{-2(\beta_{P,m} - 0.6298)}} \]

The probability score of the edge segment of the chosen pixel \( P \) can be written as
\[ \Theta_{\text{edge}} = \frac{\sum_{P \in \text{edge}} \Theta_{P,m}}{N(1 + \Theta_{\text{edge}})} \]

where
\[ \Theta_{\text{edge}} \text{ is the probability score of the edge segment} \]
\[ \Theta_{P,m} \text{ represents the probability of pixel } P \text{ lying on an edge in a movement direction } m \]
\[ \tau \text{ indicates a threshold value obtained by Otsu’s method} \]

\( \Theta_{\text{edge}} \) denotes the similarity index of the edge segment and is computed by
\[ \Theta_{\text{edge}} = \frac{\sum_{P \in \text{edge}} 1|I_{P,m} - I_{P}|}{255 \times (N - 1)} \]

The smoothness of the edge segment can be written as
\[ \Theta_{\text{edge}} = \frac{1}{N - 1} \sum_{i \neq j} \Theta(m_i, m_{i+1}) \]

where
\[ \Theta(m_i, m_{i+1}) \text{ represents smoothness measure between two consecutive pixels based on movement direction and is written as} \]
\[ \Theta(m_i, m_{i+1}) \begin{cases} |m_i - m_{i+1}| / w_3 & |m_i - m_{i+1}| \leq 180 \\ (360 - |m_i - m_{i+1}|) / w_3 & \text{otherwise} \end{cases} \]

The performance function of \( k \)-th learner, \( F_k \), can be tailored as
\[ F_k(\text{edge}) = \frac{\Theta_{\text{edge}}}{1 + \Theta_{\text{edge}}} \]

Detection process

An initial population of learners is obtained by generating random values within their respective limits to every individual in the population, for each pixel, whose \( E_{P,m}^{\text{thin}} \) value is greater than Otsu’s threshold value of \( \tau \). The \( F \) is calculated by considering grade points of each learner as connectivity angles, and the teaching, learning and avoiding phases are performed for all the learners in the population with a view of maximizing their performances. The iterative process is continued till convergence. The flow of the proposed method for obtaining the optimal edge map is shown in Fig. 2.

Results and discussion

The proposed method has been tested on a few real life images of airplane, egg, lifting body and Saturn [27], which are shown in Fig. 3. The size of these images is 256 \times 256 pixels and the resolution is 8 bits per pixel. With a view of comparing and studying the performances of the proposed method, a meta-heuristic robust method involving ACO [17] and two classical

| Table 1 | List of parameters. |  |
|---------|-------------------|---------|
|         | \( w_1 \)        | \( w_2 \) | \( w_3 \) | Sigma       | Threshold values |
|         | Real life images  | Skin images |
|         | Low     | High | Low | High |
| Proposed method | 90      | 40   | 1800 | –       | –     |
| Canny   | –       | –    | –   | 1.4142  | 0.04  |
| Sobel   | –       | –    | –   | –       | 0.1   |
## Improved teaching–learning based robust edge detection

### Fig. 4

Results of skin lesions. (a) Without any noise; (b) with Gaussian noise; and (c) with Impulse noise.

| Test Image | Proposed Method | ACO [17] | Canny [10] | Marr Hildreth [28] |
|------------|-----------------|----------|------------|-------------------|
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) |
| ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) |
| ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) |

(a) without any noise

(b) with Gaussian noise
operators of Canny [10] and Sobel [8] is also applied to these test images for obtaining the edge maps. The heuristically chosen parameters $w_1$, $w_2$ and $w_3$, required in Eqs. (9) and (16), the scale of sigma parameter and the threshold values for Canny and Sobel operators are given in Table 1. These parameters are found to yield satisfactory results for all the chosen test images even under noisy environment.

The resulting edge maps, obtained by the proposed method for real life images without any artificial noises, are presented in Fig. 3(a). The results of the ACO, Canny and Sobel operators are also included in the figure. The visual comparison of these edge maps clearly indicates that the edges detected by the proposed method are more complete and thin. The performance of the ACO, Canny and Sobel operators is found to be good for these test images but the edge obtained by ACO is not thin.

In order to study the performance under noisy environment, these images are corrupted by Gaussian and Impulse noises with a variance of 0.05. The ED algorithms are then applied to these corrupted images without applying any filtering with a view of studying the performance under noisy environment. The edge maps of the corrupted real life images are presented in Fig. 3(b) and (c) for Gaussian and Impulse noises respectively. The visual comparison of these figures clearly indicates that the proposed method and ACO are able to reject both the Gaussian and impulse noises in obtaining the true edge maps, which are found to be similar to edge maps of uncorrupted images of Fig. 3(a).

The edge maps obtained by Canny operator are unclear, found to be distorted and deviate widely from the true edges for all the corrupted images with Gaussian and impulse noises. The deviations, while comparing with noiseless case, are more pronounced in Gaussian noises, while for impulse noises, they are comparatively lower. In case of Sobel operator, the distortions in the edge maps are comparatively lower than those of Canny operator. It can also be observed from these figures that the performance of Sobel is better for Gaussian noises than impulse noise environment. The qualitative visual analysis clearly indicates that the proposed method is complete, thin and robust in rejecting the both Gaussian and impulse noises. Though the ACO is reasonably good in rejecting both Gaussian and Impulse noises, it cannot produce thin edge maps.

In the light of the fact that the proposed method performs much better than those of the existing methods, it is necessary to quantitatively analyse the results. The objective performance of ED was generally performed as a measurement of accuracy of the edge maps against an ideal ground truth image. As the ground truth images are not available for these real life images, the objective comparison is not made for these edge maps. In order to quantitatively measure the accuracy of the edge maps, the proposed method is applied to another set of medical images containing skin lesions with ground truth as shown in Fig. 4. The figure also includes the test images with Gaussian and Impulse noises. The edge maps are also obtained by ACO [17], Canny [10] and Marr_Hildreth method [28,29] with a view of studying the performances.

The resulting edge maps, obtained by the proposed method, ACO, Canny and Marr_Hildreth methods for the medical images without any noises, with Gaussian and impulse noises are presented in Fig. 4(a)–(c) respectively. The visual qualitative analyses of these figures confirm the findings of the aforesaid study on real life images. Many methods exist for performing the objective measurement, each aiming to provide the optimal method of measuring similarity to the ideal output. Among them, Pratt’s Figure of Merit (FOM) has been popularly used [30]. It lies in the range of (0–1) and can be evaluated by the following equation. A larger value, nearer to 1, indicates good performance.
where

\[ FOM = \frac{1}{\max(I_I, I_A)} \sum_{i=1}^{tnp} \frac{1}{1 + \alpha d(i)} \]  

(18)

and rapidly decrease with increase in noise level. The decay of FOM of ACO is slightly inferior to proposed method but better than Canny and Marr_Hildreth. It is very clear from these results that the proposed method is less affected by the increased noises compared to other methods, thereby establishing that the proposed method is robust.

The edge maps are also obtained by varying the scale of sigma parameter of Canny operator in the range of 0–2.6 and their FOM values are evaluated for the three skin lesions with and without Gaussian and Impulse noises. The FOM values are graphically compared with those of the proposed method in Fig. 6. The results clearly indicate that the performance of Canny operator with different scale of sigma parameters is inferior to the proposed method. The aforesaid discussions clearly indicate that the proposed method outperforms the existing approaches and is suitable for ED of digital images, especially in noisy environments. The average
The execution times of all the methods are given in Table 2. It is well known that Canny and Sobel operators are very efficient as they involve first order derivatives. The Marr_Hildreth method involves second order derivatives and takes little higher execution time. The evolutionary algorithms such as ACO and ITLO involve huge computations over sufficient number of iterations and require huge execution time. While comparing the execution time of the proposed method with ACO based method, the proposed method is 1.39 times faster, besides offering robust solution.

Conclusions

TLO, comprising two phases of teaching and learning, is a population based algorithm that simulates the teaching–learning process in the classroom. The ‘Teaching Phase’ represents learning from the teacher and ‘Learning Phase’ indicates learning by the interaction between learners. The ITLO has been developed by including a third phase denoted by “Avoiding Phase” that helps to keep the learners away from the worst students with a view of exploring the problem space more effectively and escaping from the sub-optimal solutions. The ED problem of digital images has been formulated as an optimization problem and solved using the ITLO. The developed method has been applied on both the real life and medical images and the edge maps have been obtained. The results clearly exhibit that the developed method is robust in producing the edge maps even under noisy environment.

Conflict of interest

The authors have declared no conflict of interest.

Compliance with Ethics Requirements

This article does not contain any studies with human or animal subjects.

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Improved teaching–learning based robust edge detection

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