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Enhanced Medical Plant Leaf Edge Detection Method using Non-Linear Constrained Optimization

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Abstract

The accuracy of the higher level of image processing depends primarily on edge detection which is a lower level of image processing task. The accuracy of medical plant leaf edge detection determines the success of the applications developed based on computer vision and machine vision for object recognition and scene interpretation from an image. It is essential to have an effective and definite edge detection method with accurate edge information. This research paper proposes to identify the edges using constrained optimization on a medical plant leaf. The penalty method is a nonlinearly constrained optimization technique used for solving both equality and inequality constraints. It was used to solve the constrained problem by converting it into an unconstrained problem using the penalty function. Nelder mead algorithm which is a derivative-free unconstrained optimization method was used to solve the unconstrained problem to obtain optimal edge regions from an image. In this paper Receiving Operating Characteristics (ROC) curve analysis was used for the performance analysis to justify the proposed method's accuracy.

Disciplinary: Computer Engineering, Digital Image Processing

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1 Introduction

Edge is a boundary that differentiates the foreground object from the background of an image. Edges preserve basic information about the image and edge detection is considered an active research field in the image analysis domain [1]. It is an essential task required for image analysis and computer vision to classify any objects from the scene with higher accuracy. It contains information that is significant for a higher level of image processing [2]. It is easier to identify the Region of Interest (ROI) and to measure the physical properties of the required area, perimeter and shape accurately from an image when the edges are identified exactly. In short, edges are the discontinuities found in an image with a rapid change in pixel intensity value. There are several methods related to edge detection starting from first order-based methods to recent innovative techniques like genetic algorithms, bio-inspired computing and so on [2]. Traditional edge detection methods are based on the first-order derivatives that operate at every pixel position in an image. Roberts, sobel and prewitt are the edge detection techniques that are computed based on the first-order derivatives. Generally, these methods are weak towards noise and show poorer performance when the image is influenced by noise [3]. Methods based on second-order derivatives were developed to overcome these disadvantages. Second-order derivatives are capable to distinguish between edges and the noise though both are considered as an unexpected change in pixel intensity value [4].

This paper proposes an edge detection method of medical plant leaf that produces an exact edge map with edge information. It overcomes problems like false edges, missing edge regions, discontinuity in edges and noises. The proposed method uses the concept of constrained optimization to focus on the problem of edge detection as an optimization problem. Constrained optimization helps to produce an optimized edge map with higher accuracy. Edges are continuous, long, and definite with no false edge regions. Mathematically, constraint optimization is used for solving optimization problems that are restricted by constraints in the objective functions. Penalty method, Lagrange multiplier, and augmented Lagrange multiplier are the common nonlinear constrained optimization used for solving the optimization problem. The penalty method was used in the proposed method as it was flexible to both the equality and inequality constraints.

2 Literature Review

2.1 Penalty Method

The penalty method [5] usually converts the constrained problem into the unconstrained problem by adding a penalty function to the objective function for ideal convergence. The penalty method with equality constraints has a constraint value equal to zero. The penalty method with inequality constraints has a constraint value less than or equal to zero for the minimization problem and has a constraints value greater than or equal to zero for the maximization problem. The penalty function uses a penalty multiplier to convert the problem into an unconstrained method. The penalty multiplier uses the penalty parameter (μ) a scalar value that is multiplied along with the constraint to obtain a new objective function [5].

After deriving the new objective function, the next step is to optimize the new objective function using derivative-free unconstrained optimization techniques. Nelder-mead, also known as the direct or simplex search method is applicable for optimization problems where the derivative methods are complex, expensive and not applicable [6]. This method is also useful when the function is discontinuous and noisy. It requires only function evaluation and not derivative values for optimization. To solve a minimization problem, f is considered as a real-valued function with simplex S which is a polyhedral set with n+ 1 vertex {a1, a2, a3.... an+1}. An associated matrix (A(S)) with linear independence in Rn (set of real numbers) is,

$$A(S) = [a2 - a1, a3 - a1, ...an+1 - a1] \quad (1).$$

The simplex is non-degenerate if A is a nonsingular matrix where its vertices are not coplanar. This algorithm searches for appropriate value through iterations. It compares the function values on the vertices and removes the vertex with the worst function value and then replaces it with another vertex point with a better value. The selection of a new point is based on the reflection, contraction, shrinkage and expansion of the simplex along the line that joins the worst vertex and the centroid of the other vertices. Let f(a1), f(a2), f(a3),....... f(an+1) be an ordered vertices at any specific step of the algorithm and it can be expressed as,

$$f(a1) \leqslant f(a2) \leqslant f(a3) \leqslant ...... \leqslant f(an+1) \quad (2),$$

where f(a) is a function for the constraints with a as the constraints. Thus the new points replace the worst vertex to achieve the solution for an optimization problem.

2.2 Lagrange Multiplier Method

Lagrange multiplier is a powerful method used to solve constraint optimization with equality constraints [7]. Instead of using a penalty function like the penalty method, lagrangian function is used to solve the optimization problem. Lagrangian function uses a Lagrange multiplier to convert the constrained problem into an unconstrained problem. Lagrange multiplier is an unknown scalar value used to combine with the objective function to form a new objective function. The number of Lagrange multipliers required for a function is determined by the number of equality constraints found in the function. If there are Z equality constraints then the Lagrange multiplier required to solve the problem is also Z.

Let the constrained optimization problem subject to the equality constraint be expressed as

$$\min f(x) \text{ subject to } Ct\,(x) = 0,\ x = (x1..xn)\ T \quad (3),$$

where f(x) is the objective function, C is the constraint, x is a set of values in the vector and n is a number of elements in x. Next, to obtain a new objective function called lagrangian function, Lagrange multiplier (ƛ) is added to the existing objective function as

$$L\,(x, ƛ) = f(x) + \sum_{I=1}^{Z} ƛ1\ C1(X) \quad (4),$$

where is a scalar value of the lagrange multiplier added to the below equation. Finally to solve the minimization problem, partial derivatives of the new objective function (L(X,ƛ)) is set to zero as,

$$\eth/\eth X\ L(X, ƛ) = \Delta f(x) + \sum_{I=1}^{Z} ƛ1\Delta\ C1(X) = 0 \quad (5),$$

$$\eth/\eth X\ L(X, ƛ) = C(x) = 0 \quad (6).$$

This method produces an optimal solution for problems with equality constraints.

2.3 Constrained Optimization

Constrained Optimization is used for finding the optimal point either as minimization or maximization in an objective function [8]. It is influenced by two important factors called criterion and constraints. Criterion expresses the purpose of optimization either as minimization or maximization of objective function. Constraints are the restrictions imposed over the input variables of the objective function that express relationship among these input variables in mathematical terms. It can be of either equality or inequality constraints. Constrained optimization is formulated mathematically as

$$\begin{cases} \text{minxeɒn } f(x) \quad ca\,(x) = 0,\ a\ £\ E \\ da\,(x) \geqslant 0,\ a\ £\ I \end{cases} \qquad (7),$$

where f(x), c(x), d(x) are the real-valued functions on the subset of Rn (Real value numbers), f(x) is an objective function for the minimization problem, c(x) is set of equality constraints and d(x) is set of inequality constraints, E and I are set of values for c and d with a as the number of constraints. An optimization problem with constrained variables is solved by converting the problem into an unconstrained optimization. But the algorithmic approach of the unconstrained method is not well suited for these constrained methods after conversion as it causes Maratos effect i.e., it causes a lack of convergence.

Non-linear methods like the penalty method [9], Lagrange multiplier method and augmented Lagrange multiplier method are used in constrained optimization to attain optimal results with a faster convergence rate. The penalty method is very much of use to solve the constrained problem either with equality or inequality constraints and Lagrange method is concerned only with the problem related to equality constraints. Augmented Lagrange method is similar to that of the penalty method but the major difference is that it adds a constant term to the unconstrained objective function that is similar to that of Lagrange multiplier.

3 Proposed Methodology

Identifying the exact edge region is characterized by factors like edge strength, non-influence of noise, continuity and smoothness in an edge. The proposed method uses the penalty method of constrained optimization to identify the edges that satisfy the characteristics of edges in medical plant leaf. Implementation of the proposed method was carried out using Matlab R2021a. The proposed algorithm steps as follows,

Algorithm

Step 1: Consider an Input medical plant leaf image.

Step 2: Initially determine values for error tolerance and penalty parameters.

Step 3: Convert the RGB image into a grayscale image.

Step 4: Performing median filtering to reduce unwanted information in an image.

Step 5: Calculate the gradient for the grayscale image at x and y directions.

Step 6: Consider the pixel values of x and y direction gradient images as input for the objective function to obtain the optimal solution.

Step 7: Determining an objective function for finding an optimized edge region.

Step 8: Finding a new objective function using a penalty function to convert the constrained problem into the unconstrained problem.

Step 9: Applying Nelder mead or simplex search method, a derivative-free optimization method over the penalty function to find the optimal solution point.

Step 10: Iterating each pixel in x and y direction of the gradient simultaneously in step 9 until the convergence point is reached.

Step 11: All the pixels in both the x and y gradients are optimized.

Step 12: Optimized gradient images are combined to calculate the magnitude of the image so as to obtain the enhanced edge map of the image.

3.1 Gradient Calculation

The gradient was used to find the edge strength and direction at each pixel location in an image. Initially, the image in RGB color space was converted into grayscale for easy manipulation. Image enhancement using median filtering was performed to remove the unwanted information like noises in an image [9]. The gradient of an image was calculated using first-order derivatives at every pixel position in an image [8].

3.2 Applying Penalty Method

The penalty function was used for finding the optimal edge points in an image. The penalty method was considered as it suits best for both equality and inequality constraints. The penalty method solves the objective function with regard to x and y derivatives of the image. The main objective of the penalty method was to convert constrained optimization into unconstrained optimization. The intensity value of the pixels in x and y derivatives were considered as input to the objective function. Penalty parameters (μ) were added to the objective function to find the new objective function for converting the problem into unconstrained optimization. Penalty function method first formulates a new objective function with no constraints using the penalty parameters. Penalty function for the constrained problem with equality and inequality constrained equation is as follows,

$$\text{minimize } \{f(x) : x \text{ £ } T\}$$

where f is a continuous function and T is a constraint.

$$\text{minimize } f(X) \text{ ¥ } f(x) + \mu \textstyle\sum T \; ST(x) \quad (8),$$

where μ is a penalty multiplier that contains a positive constant value and ST is a function satisfying the condition given in the following equation,

$$ST(X) \begin{cases} = 0 \text{ if x satisfies T} \\ > 0 \text{ otherwise} \end{cases} \quad (9).$$

New objective functions are formed using penalty parameters that are multiplied by a measure of violation which is zero when the constraints are not violated in the region and is non-zero when violated from the region. A higher penalty parameter or an unnecessary increase in penalty parameter value leads to slower convergence [7].

A constrained problem converted into an unconstrained problem was solved using the derivative-free optimization method. Derivative-based unconstrained methods were not used for solving the new objective method due to constraint terms and the gradient of the new objective function. Constraint terms found along with the objective function are zero when the value of x lies within the prescribed region else the value of the constraint term increases steeply. The gradient of the new objective function does not provide any useful information regard to direction and magnitude. These two reason causes a lack of convergence and effectiveness in the derivative-based unconstrained method. Hence nelder mead a derivative-based method was used for solving the unconstrained optimization problem.

Nelder mead method [10] or the simplex search method iterates pixel value in the objective function to get an optimal value. Error tolerance rate and the number of iterations were fixed to check the convergence criteria. The initial starting point for optimization was started from the first pixel point in the x and y derivatives of the image. These values were taken into the new objective function and it was iterated until the convergence point was reached. The old pixel value is now replaced with the new pixel value after reaching convergence in that pixel position. Now the iteration was stopped and the next pixel value was taken for calculating the optimal value. Similarly, this step was processed for all the pixel points in the image. Finally after optimizing both the gradient images, the magnitude of the image was calculated using

$$Mag(x,y) = \sqrt{(Ix2 + Ix2)} \quad (10),$$

where Ix and Iy are x and y direction derivatives of the image. The direction of image gradient was calculated using,

$$D(x,y) = \tan^{-1}[Ix / Iy] \quad (11).$$

Thus x- derivatives and y-derivatives of the gradient were combined to form an optimized edge region for the image.

4 Result and Discussion

Implementation of the proposed method image was taken from Tulsi medical plant image. Evaluation of the proposed method and its comparison with other existing methods were done using quantitative metrics [10]. Receiver Operating Characteristics (ROC) analysis was the measurement tool used for comparing the performance of the proposed method along with other existing methods like Robert, sobel, prewitt, canny, log and susan. ROC curve analysis was formed by plotting the true positive rate against the false-positive rate. ROC was calculated for an image by comparing the output of the edge method along with the standard ground truth image [11].

True positive rate (TPR) also referred to as sensitivity or recall was calculated using,

$$TPR = TP/(TP+FN) \quad (12),$$

where TP is the true positives which are the number of edges that are correctly identified as edges between two images and FN is false negatives which are the number of non-edges that are wrongly identified as edges.

False-positive rate (FPR) also referred fall-out or (1- specificity) was calculated using,

$$FPR = FP/(FP+TN) \quad (13),$$

where FP is false positives which are the number of edges that are incorrectly identified as edges between two images and TN is true negatives which are the number of non-edges that are correctly identified as non-edges. Area under ROC curve (AUC) was used to measure the performance of an edge method from the ROC curve and has values that lie between zeros to one. It was calculated by differencing the area above the curve and the area below the curve. It was calculated using,

$$AUC = \int_l^u f(x)\,dx \quad (14),$$

where l and u are the lower and upper bound values in the axis of the ROC curve with the function f(x) that lies partly above the curve and partly below the curve. AUC curve with a higher value indicates better performance and a lower value indicate poor performance. It was noted that the performance of the proposed method using the penalty method had a higher accuracy when compared with other existing methods.

Figure 1: Input image

Figure 2: Sobel operator output (Existing)

Figure 3: The proposed method output

5 Conclusion

An enhanced medical plant leaf edge detection method has been proposed in this research paper using the penalty method which is a non-linear constrained optimization technique. The penalty method applies the penalty function over the objective function to obtain a new objective function using the penalty parameter which converts the constrained function into an unconstrained optimization function. A derivative-free optimization method, nelder-mead algorithm was used to solve the optimization problem for the images to obtain an exact edge map. Performance evaluation and comparison of the proposed method were done using ROC curve analysis. It was noted that edge detection by the proposed method was better when compared with other existing methods.

6 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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