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An Improved Canny Edge Detection Algorithm Based on Type-2 Fuzzy Sets

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Abstract

Canny's edge detection algorithm is a classical and robust method for edge detection in gray-scale images. The two significant features of this method are introduction of NMS (Non-Maximum Suppression) and double thresholding of the gradient image. Due to poor illumination, the region boundaries in an image may become vague, creating uncertainties in the gradient image. In this paper, we have proposed an algorithm based on the concept of type-2 fuzzy sets to handle uncertainties that automatically selects the threshold values needed to segment the gradient image using classical Canny's edge detection algorithm. The results show that our algorithm works significantly well on different benchmark images as well as medical images (hand radiography images).

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1. Introduction

Most of the image processing applications require image segmentation to subdivide the images into its constituent regions or objects. Image segmentation algorithms generally are based on one of two basic properties of intensity values: similarity and discontinuity. Edge detection is by far the most common approach for detecting meaningful discontinuities in gray level. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning zero in uniform regions. The popular edge detection techniques involve masking based operators like Sobel, Prewitt, Roberts etc. to compute the gradient at each point of the image. Also, Laplacian of Gaussian (LoG) is a useful method for edge detection which works on the second derivative of the image.

Canny's edge detection algorithm [1] is well known as the optimal edge detection method. It works on three main principles: low error rate, well localization of edge points and one response to a single edge. To enhance the older edge detection methods, Canny proposed two new techniques in his algorithm, non-maximum suppression and double thresholding to select the edge points. However, these two thresholds

used to segment the gradient image are set experimentally. An adaptive edge detection method based on Canny's operator was presented in [2], which used Otsu's thresholding method to determine the threshold values. In [3], the authors proposed an edge detection method based on fuzzy reasoning which incorporated human visual characteristics. Xiao et al. [4] proposed an improved version of the Canny's edge detector specially designed for images distorted by Gaussian noise. In [5], the Canny's edge detector was used to find the best region growing method for medical image segmentation.

Due to poor illumination, low image quality or other possible factors, the boundary between different regions of an image may be vague. It makes most of the edge points uncertain, resulting improper determination of the points by the state-of-the-art methods. According to [6], the degree of fuzziness of an image is one of the key factors affecting the performance of the determination of the threshold values for image segmentation. Evidently the uncertainty present in an image makes its gradient image uncertain too. In such cases, the process of choosing the threshold values from the gradient image histogram for edge detection becomes difficult. In this paper, we propose an algorithm based on type-2 fuzzy sets to automatically choose the threshold values for Canny's edge detection method. The proposed scheme minimizes the uncertainty involved in the thresholding procedure using Ultra-fuzziness index.

2. Proposed Scheme

2.1. Canny's Edge Detection Algorithm

Canny's classical algorithm has good performance in edge detection, localization and only one response to a single edge. The Canny's edge detector follows the below mentioned steps,

- (a) It first smoothes the image using Gaussian filter to eliminate the noise.
- (b) It then finds the image gradient using Sobel operator to highlight regions.
- (c) Followed by suppression of any pixel that is not at the maximum (non-maximum suppression).
- (d) Hysteresis is used to track along the remaining pixels that have not been suppressed. Double thresholding method uses two thresholds T1 and T2 which are used to classify the gradients in three groups,
 - Gradients > T2 : definitely an edge point
 - Gradients < T1 : definitely a non-edge point
 - Otherwise, the decision is taken depending on the direction of the point and existing edge paths.

It is difficult to find the threshold values T1 and T2 automatically, especially when the image boundaries are vague.

2.1. Threshold Segmentation using Type-2 Fuzzy Logic

If the degree of fuzziness in data points is high, then the quotient of ambiguity in gradient image data will also be high, which will make the threshold selection difficult. The procedure stated in [6] depends on finding the *ultrafuzziness* (degree of fuzziness of a type-2 fuzzy set) value using the upper ($\mu_U(x)$) and lower ($\mu_L(x)$) membership functions of the *footprint of uncertainty (FOU)* associated with the interval type-2 fuzzy set representing the data (*figure 1a*). By sliding the membership function over the histogram as shown in *figure 1b*, the value of the *ultrafuzziness index (UF)* is calculated using the following formula

$$UF = \frac{1}{N} \sum_{\min}^{\max} h(x)[\mu_U(x) - \mu_L(x)] \quad (1)$$

(1), where, N is the total count of data points present in the histogram, \min and \max are the minimum and maximum value on of the histogram x -coordinate, $h(x)$ is the histogram value at point x .

The upper and lower membership functions are constructed using the hedge operator (α) on a skeleton basic membership function ($\mu(x)$) as follows (equation 2 and 3).

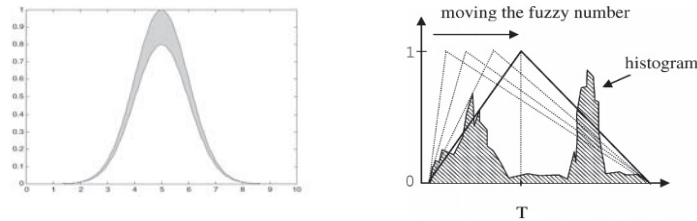
The position of the center of the membership function that returns the maximum ultra fuzziness corresponds to the optimal threshold value that best partitions the histogram into two homogeneous

$$\mu_U(x) = [\mu(x)]^{1/\alpha} \quad (3)$$

$$\mu_L(x) = [\mu(x)]^\alpha \quad (2)$$

modes.

Fig. 1. (a) FOU of an interval type-2 fuzzy set; (b) Sliding the membership function on the histogram



In this paper we propose an algorithm to choose the threshold values $T1$ and $T2$ automatically to be used in the Canny's edge detection algorithm. The method uses the single threshold selection technique from image histogram using type-2 fuzzy logic, but works on the gradient histogram produced by the Sobel operator. The gradient histogram (spread from $range1$ to $range2$) is divided into two parts with threshold T , which nearly identifies the range for non-edge points ($range1$ to T) and edge points ($T + 1$ to $range2$). The part of the histogram denoting non-edge points is again divided into two parts by $T1$: definitely non-edge points ($range1$ to $T1$) and uncertainly non-edge points ($T1 + 1$ to T). Similarly the edge portion is divided into uncertainly edge points (T to $T2$) and definitely edge points ($T2 + 1$ to $range2$) using threshold $T2$. These thresholds $T1$ and $T2$ are passed to Canny's algorithm to get the final edges. So the decision for the two classes, uncertainly non-edge points and uncertainly edge points i.e. the range ($T1$ to $T2$), are taken according to their direction contributing to the existence of an edge path. The simple algorithm is given below,

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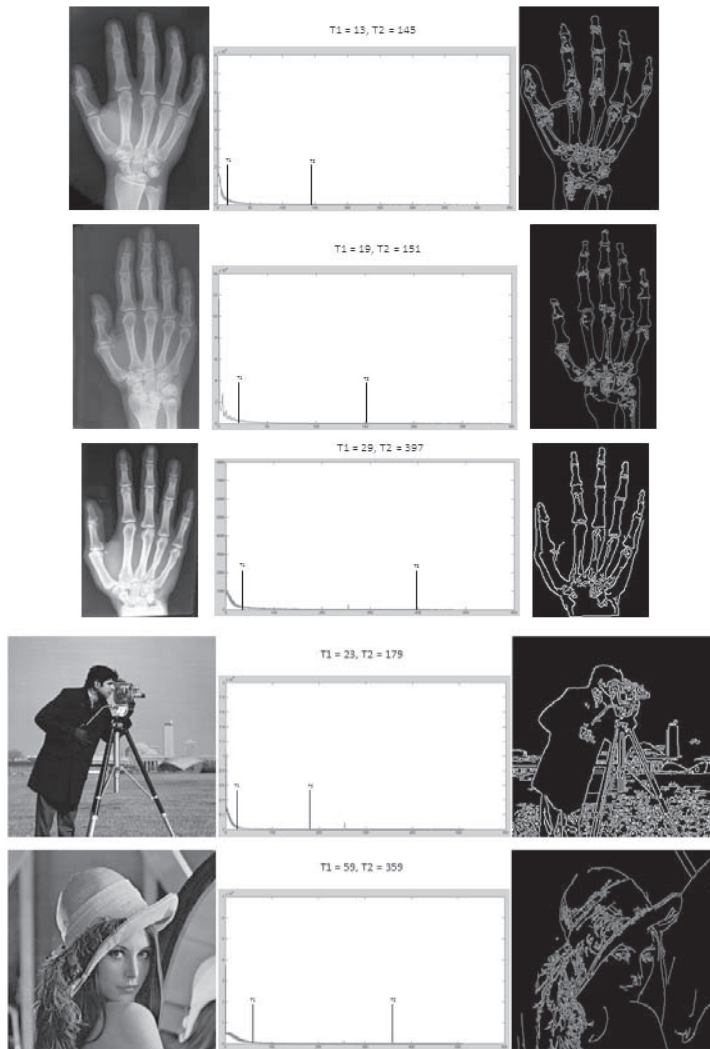
array histogram[ ]
function gradientThreshold (range1, range2)
    T = type2Threshold (range1, range2)
    if T > range1
        T1 = type2Threshold (range1, T-1)
    else
        T1 = T
    if T < range2
        T2 = type2Threshold (T+1, range2)
    else
        T2 = T
    CannyEdgeDetection (T1, T2)
end function

```

We have used the skeleton membership function as the simple triangular function and the value of hedge as 2 in the *type2Threshold* method.

3. Results and Discussion

We have chosen medical images of hand radiography with uneven illumination, benchmark images and contrast variant images for applying the proposed method. The original images and their edge detection results are shown in *figure 2* indicating the values of $T1$ and $T2$ which are determined automatically.



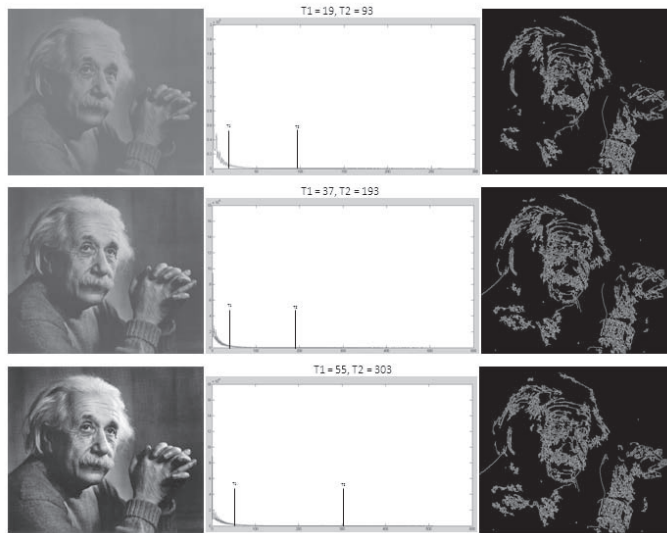


Fig. 2. Results of type-2 fuzzy set based algorithm

4. Conclusion

It can be seen from the results that, the type-2 fuzzy logic based threshold selection method selects effective threshold values to be used in the Canny's edge detector. The proposed algorithm takes care of the uncertainty involved in the image quite efficiently. To serve the purpose of particular applications in edge detection, in spite of choosing the threshold values randomly, this method is supposed to give a good starting point for selection of the threshold.

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