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NO-REFERENCE IMAGE BLUR DETECTION SCHEME USING FUZZY INFERENCE

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ABSTRACT. The scanned document images from hand holding cameras may be deformed with image degradations factors such as blur and noise due to limitations of these hand held devices. Image blur is the common cause of image degradation. In this paper, Fuzzy inference based blur detection procedure is proposed for document images. The proposed algorithm achieves 95% accuracy that is superior to other prominent algorithm in the no-reference blur detection area.

1. INTRODUCTION

Document scanning by the use of any handy digital cameras like mobile camera has a numerous advantages over scanner-based input. These cameras are portable, easy to transport and easy to handle. Inexpensive and multipurpose digital cameras make it promising capture a large range of documents effortlessly and speedily. However, most of the times images captured by handy digital cameras can be degraded by blur. Blurring is one of the most common image deformation in digital imaging. Image quality, particularly for document images

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where the text in document is certainly vanished owing to image blur degradation [1].

An example of sharp image and a blurred image is shown in Figure 1. It is evident from comparison of these images that blur makes a document image unreadable. This paper is structured as follows in subsequent sections. Section 2 discusses image degradation and blur models. Proposed methodology is discussed in Section 3. Finally, results and experiments and conclusion is presented in Section 4 and Section 5 in that order.

FIGURE 1. (a) Sharp image and (b) its blurred version

2. IMAGE DEGRADATION MODEL

The image blurring procedure can be described by the following convolution method as discussed in [2]

$$g(x, y) = f(x, y) * h(x, y) + \eta(x, y).$$

Here, $g(x, y)$ is the blurred image, $f(x, y)$ is the original document image, $h(x, y)$ is the blur function, and term $\eta(x, y)$ is the additive noise. In image Fourier domain (frequency domain) the above model can be expressed as

$$G(u, v) = F(u, v)H(u, v) + N(u, v).$$

The Point Spread Function (PSF) of motion blur is defined as

$$h(x, y) = \begin{cases} \frac{1}{L}, & \sqrt{x^2 + y^2} \leq \frac{L}{2} \& \frac{x}{y} = \tan\alpha \\ 0, & \text{otherwise} \end{cases} .$$

The PSF of defocus blur is defined as

$$h(x,y) = \begin{cases} \frac{1}{\pi R^2}, & \sqrt{x^2+y^2} \le R \\ 0, & \text{otherwise} \end{cases}.$$

3. Blur detection methodology

This scheme is inspired by Intentional Blur Detection (IBD) method [3]. In this method, at first by two different low pass filters, in horizontal and vertical directions, compute the blur degradation factors in horizontal BF_Hor and vertical directions BF_Ver as proposed. A simplified blur degradation detection flow chart is given in Figure 2.

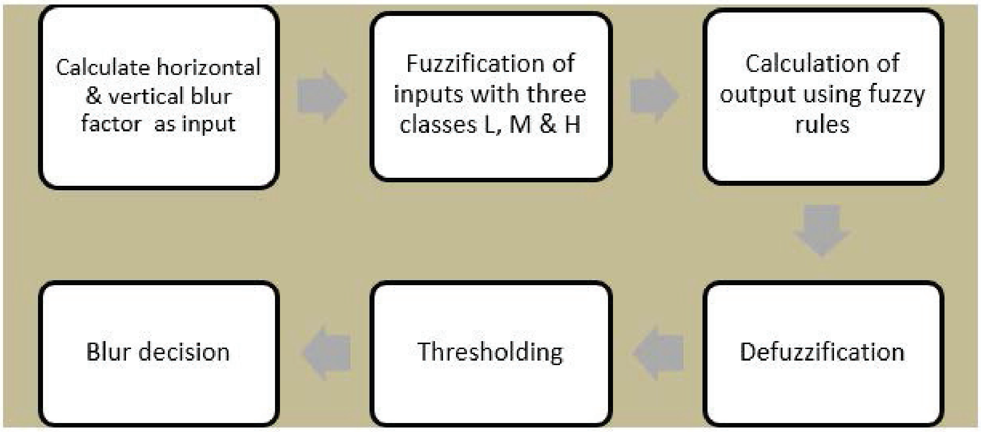

FIGURE 2. Proposed methodology for no-reference image blur detection scheme using Fuzzy logic

By considering these blur degradation factors and a Fuzzy inference based idea, two calculated parameters are utilized as input to the Fuzzy inference based system. The Final decision about blur degradation is based on the result of this Fuzzy inference based scheme. Suitable Fuzzy inference based membership functions are designed for Fuzzy inference based system inputs. We define the membership function as the Sigma and Trapezoidal functions [4, 5]:

$$\mu(z) = \begin{cases} 1 - \frac{a-z}{c}, & \text{if } a-c \le z < a \\ 1, & \text{if } a \le z < b \\ 1 - \frac{z-b}{d}, & \text{if } b \le z < b+d \\ 0, & \text{otherwise} \end{cases}.$$

$$\mu(z)=\begin{cases} 1-\frac{a-z}{b}, & \text{if } a-b\le z\le a \\ 1, & \text{if } z>a \\ 0, & \text{otherwise} \end{cases}.$$

To utilize these membership functions, first both blur degradation factor values are mapped in the interval of $[0,1]$. Then both of the projected values are categorized to one class among the low, medium, or high classes. The horizontal Blur Degradation Factor (BDF) classes are represented as BFHor_L, BFHor_M and BFHor_H.

To isolate dissimilar BFHor classes four dissimilar thresholds a_1, b_1, a_2, and b_2 are applied. So that, if BFHor value is the interval of $[0, b_1]$, then the equivalent blur degradation factor is categorized to BFHor_L, for the range of $[a_1, b_2]$, the blur degradation factor is categorized to BFHor_M, and lastly for the range of $[b_2, 1]$, blur degradation factor is categorized to BFHor_H. The similar function and classes are defined for BFVer value. In Figure 3, the well-defined classes and Fuzzy rule based membership functions are presented.

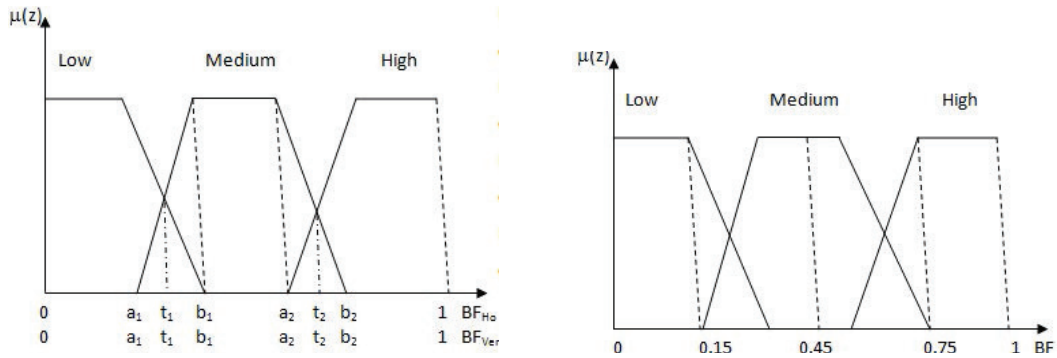

FIGURE 3. Input and Output Membership Function for blur degradation factors in horizontal and vertical directions

The yield of Fuzzy rule based system describes up-to what degree an image is blurred. This Fuzzy inference based system is used to categorize to a particular classes out of three classes by the defined Fuzzy rules. The initial class, BFL correspond to image with small probability value to be blurred one. In the same way, BFM corresponds to medium probability and BFH relates to high likelihood. Output membership functions are presented in Figure 3(b). If BFHor value of an image being equal to t1, and gradient be equal to t_2, the Fuzzy rules are decided as the following:

F. Rule 1 If t1 in BFHor_L and t2 in BFVer_L then BDF categorized to BFL.
F. Rule 2 If t1 in BFHor_L and t2 in BFVer_M then BDF categorized to BFL.
F. Rule 3 If t1 in BFHor_L and t2 in BFVer_H then BDF categorized to BFM.
F. Rule 4 If t1 in BFHor_M and t2 in BFVer_L then BDF categorized to BFL.
F. Rule 5 If t1 in BFHor_M and t2 in BFVer_M then BDF categorized to BFM.
F. Rule 6 If t1 in BFHor_M and t2 in BFVer_H then BDF categorized to BFH.
F. Rule 7 If t1 in BFHor_H and t2 in BFVer_L then blur BDF categorized to BFM.
F. Rule 8 If t1 in BFHor_H and t2 in BFVer_M then BDF categorized to BFH.
F. Rule 9 If t1 in BFHor_H and t2 in BFVer_H then BDF categorized to BFH.

Defuzzification is finished using the following equation:

$$\text{Blur Factor}(BF_{\text{Final}}) = \sum(BF_j \times C_j),$$

where $BF(j)$ is the pixel membership value in class j, and C_j is the jth output class center. Corresponding Figure output membership, classes center are determined as the following: $CL = 0.15$, $CM = 0.45$, $CH = 0.75$. BF_{Final} is the probability applied for absolute image categorization as blurred or non-blurred. A blur degradation factor with probability larger than a threshold is categorized as blurred; otherwise, it is categorized as sharp. A usual suitable threshold value is 0.4.

4. Experiment and results

To explain the procedure an illustration is described below. Assume for an image BFHor value equal to 0.75 and its BFVer value is equal to 0.30. Considering the membership functions and these values as explained a1= 0.15, b1= 0.37, a2= 0.62, b2= 0.87, t1= 0.75, t2= 0.30 .

$$\mu(BF\_Hor_L) = 0, \quad \mu(BF\_Hor_M) = 0.5, \quad \mu(BF\_Hor_H) = 0.5,$$

$$\mu(B\_Ver_L) = 0.28, \quad \mu(B\_Ver_M) = 0.72, \quad \mu(B\_Ver_H) = 0.$$

Concerning to the calculated membership values and well-defined Fuzzy rules, it's indicated that excepting Fuzzy rules number 4,5,7, and 8, the other BF are equivalent to zero. The non-zero P-Edges are calculated as the following:

$$BF \text{ in } BF_L = \mu(BF_{HorM}) \times \mu(BF_{VerL}) = 0.5 \times 0.28 = 0.14$$

$$BF \text{ in } BF_M = \mu(BF_{HorM}) \times \mu(BF_{VerM}) = 0.5 \times 0.72 = 0.36$$

$$BF \text{ in } BF_L = \mu(BF_{HorH}) \times \mu(BF_{VerL}) = 0.5 \times 0.28 = 0.14,$$
$$BF \text{ in } BF_H = \mu(BF_{HorH}) \times \mu(BF_{VerM}) = 0.5 \times 0.72 = 0.36$$
$$BF_{\text{Final}} = (0.14 \times 0.15) + (0.36 \times 0.45) + (0.14 \times 0.15) + (0.36 \times 0.75) = 0.474.$$

Finally compared to the threshold equivalent to 0.4, mage is categorized as sharp edge point otherwise blurred. RVL-CDIP is used to evaluate the performance of the proposed blur detection procedure. This dataset is a collection of scanned documents from public records [6]. 1000 images of this dataset are synthetically blurred using motion and defocus blurs. Following table presents the results achieved with 1000 blurred and sharp images. Out of these thousand images five hundred images are sharp and others are blurred. Table 1 presents the accuracy in each case. The IBD algorithm provides 92.5% accuracy for sharp class whereas proposed method delivers 96.6% accuracy. On the other hand, The IBD algorithm provides 91.4% accuracy for sharp class whereas proposed method delivers 93.4% accuracy for blurred class.

TABLE 1. Accuracies for blur detection schemes

Class	IBD Algo.	Proposed method
Sharp Image	92.5	96.6
Blurred Image	91.4	93.4
Average	91.95	95

Figure 4 presents the comparative study of the proposed no-reference image blur detection scheme using Fuzzy logic with IBD algorithm. It is evident that proposed scheme performs better than IBD algorithm for both classes i.e. sharp and blurred.

5. CONCLUSION

In many image processing applications and specially in document image processing, it is very desirable to assess the quality of these degraded document images. In this work, a prominent blurriness/sharpness blur detection scheme is presented that utilizes Fuzzy inference. The evaluation results established the effectiveness of the proposed scheme. This blur detection work can be further extended by taking other image degradation factors in consideration.

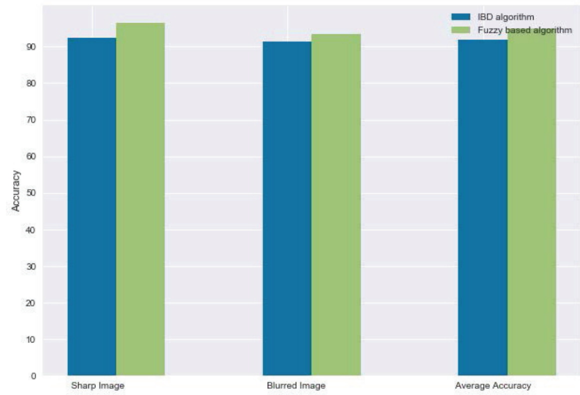

FIGURE 4. Comparative study of no-reference image blur detection scheme using Fuzzy logic and IBD algorithm

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