A New Structural No-Reference Rule Based Blur Metric for Classification of Blurred Home Photos

P. Shivakumara[1], **Basavaraj S. Anami** [2], and **G. Hemantha Kumar**[3], Non-members

ABSTRACT

Automatic classification of blurred photos from family album has drawn researchers' attention to avoid computational overhead of deblurring and measurement of blur in the photos. Therefore, the primary goal of this paper is to classify the blurred photos rather than measuring degree of blurness in the image or to deblur an image. The blur metric is proposed based on the fact that the number of Canny edge components is more than the number of Sobel edge components in blurred photos. Similarly, for non blurred photos, the number of Canny edge components is less than the number of Sobel edge components. The rules are devised based on the width of Canny and Sobel edge components to classify the blurred photos. The experimental results of the proposed metric are compared with the results of the existing methods for the purpose of evaluation.

Keywords: Sobel edge, Canny edge, Width of the edge components, Statistical parameters, Rule based blur metric, Classification, Blurred photos.

1. INTRODUCTION

Automatic classification of blurred photos from the home photo gallery is essential prior to deblurring and measuring the degree of blur in order to improve accuracy of the retrieval algorithms and to avoid computational overhead on non blurred photos. This classification could be useful in avoiding capturing blurred photos while taking the pictures using digital camera. For example, NIKON S4 camera has a feature that it gives blur warning when camera goes out of focus or defocus. However, the camera does not give warning for the blurred photos produced by motion. With this feature of classification of blurred photos, one can avoid capturing blurred photos by retaking the same photo rather than performing perceptual quality metrics to measure the blurness in the image and deblurring the blurred photo. To the best of our knowledge, in present market no such cameras are available. Besides, there are some situations, where it is not possible to retake the photos of the same scene when blurred photos produced by satellite and compression techniques. In such cases, prior to deblurring and measuring the amount of blur, classification of blurred photos is essential, which eliminates the computational overhead required for deblurring unnecessarily the non blurred photos.

With the advancement in digital imaging such as anti-shake technology, blurred photos get significantly reduced. Furthermore, users can easily view their shots with their cameras and delete photos that are not well accepted and to retake them at no cost. However, this is possible in case of defocusing and little handshake but not in case of motion blur and blur caused by satellite and compression techniques. For instance, we have experienced with the digital camera that if a small amount of blur is present in the photo, human vision system fails to notice such a blur because of great reduction in size of the actual image in preview display. Moreover, if blur occurs in certain parts of the photo, we need to operate shift and zoom in and out to fix such a blur. But, this process is time consuming and is not acceptable to common people. Hence, the automatic classification of blurred photos is essential in the field of multimedia and image processing.

There is a good amount of on going work found in literature in the field of deblurring [1, 2], developing perceptual quality metric [3, 4, 5, 6], multimedia image indexing and retrieval, advanced technology for digital cameras and inpainting [7]. However, we believe that the existing methods assume availability of blurred photos. The methods of perceptual quality metrics can be categorized into four classes that are Full-Reference (FR), Reduced-Reference (RR), No-Reference (NR) and Hybrid Quality Image Metric (HQIM). The FR works well, if the original image is available [3]. Hence, FR metrics are not suitable for classification of blurred photos. The RR metrics expect the reduced form of original photo [3]. Hence, RR metrics does not serve our purpose. The HQIM is the combination of several metrics for different artifacts such as smoothness, blocking, ringing, masking

Manuscript received on February 28, 2007 ; revised on January 31, 2008.

[1] The author is with 1Department of Computer Science, School of Computing, National University of Singapore, Singapore-117590., E-mail: shiva@comp.nus.edu.sg and hudempsk@yahoo.com

[2] The author is with Bsaveshawara College of Engineering, Bagalkot, Karnataka, India. , E-mail: anami_basu@hotmail.com

[3] The author is with Department of Studies in Computer Science, University of Mysore, Mysore, Karnataka, India. , E-mail:

and lost block [5]. This metric requires human intervention to decide the weights. Hence, it is also not suitable for automatic classification of blurred photos as it is too sensitive to weights. The NR metrics [4, 6] estimates the degree of blur based on spread of the edges by the effect of smoothing and smearing done by the filters and compression techniques. The spread of the edge is defined as the distance between the starting and ending points on x-axis of the edge. This is called local blur measure of the edge. The global blur is computed for the whole image by averaging the local bur values over all edges. However, the metric could not classify the blurred photos as the metrics work based on average of gradient values. The average of gradient values are obtained using Sobel edge detector. But, we believe that as blur increases the number of Sobel edges decreases [4]. Furthermore, it is difficult to predict the blur in photo with just average gradient value [8]. Hence, the NR metrics are not suitable for classifying blurred photos automatically. Illustrations are given in comparative study section.

To the best of our knowledge and from the above discussion, we have arrived at the following conclusions

(1) None of the above methods addressed the automatic classification of blurred photos as a two-class problem.
(2) None of the above methods addressed the problem of rotation and scaling transformations. This means that the performance of existing methods degrades when the photo is rotated or scaled. Particularly, the perceptual blur metrics as these metrics work with vertical or horizontal edges.
(3) No papers addressed the importance of blurred image classification in future digital cameras like blur warning and face tracking.
(4) None of the existing methods introduced heuristic rules for automatic classification of blurred photos.

With this in the backdrop, one can say that the automatic classification of blurred photos has great demand to meet the requirements of current real time applications such as digital camera with additional feature to avoid capturing blurred photos.

Hence, in this paper, we focus on classification of blurred photos from the database of family album. The proposed metric computes width of Sobel and Canny edge components to derive heuristic rules. The mean, median and mode are computed for the set of width of edge components to achieve more accuracy by deriving more number of rules. It is revealed from the experimental results that the proposed metric achieves 92.5% accuracy in classification.

The structure of the paper is as follows. A theoretical background for the proposed methodology is described in the section 2. Experimental results with different statistical parameters are provided in the section 3. Section 4 presents the comparative study with existing methods. Section 5 discusses the advantages and disadvantages of the proposed methods. Finally, conclusion and future work are given in the section 6.

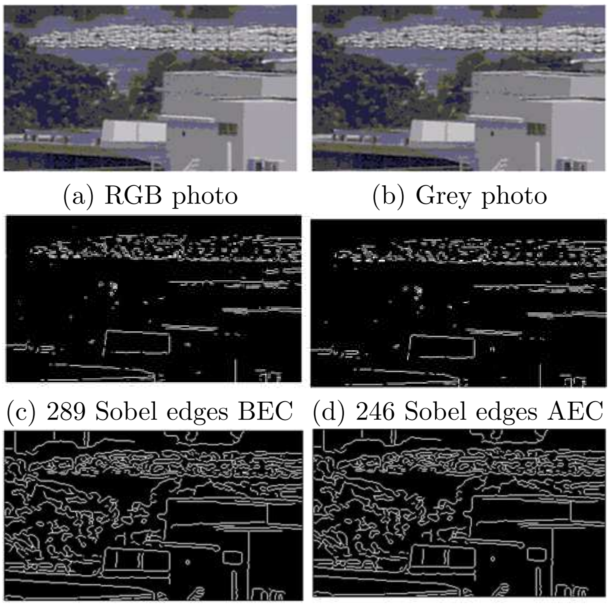
2. PROPOSED METHODOLOGY

We propose a rule-based metrics for classifying the blurred photos from the database of family album. The proposed metric works on the basis that a good edge detector must output less number of edges compared to other edge detectors for non blurred photos [9, 10]. This fact motivated us to derive new rules for classification of blurred photos. The metric obtains Canny edge and Sobel edge images for a given photo using MATLAB inbuilt functions. Let $EC = c_1, c_2 \ldots c_n$ and $ES = s_1, s_2, \ldots s_n$ be two sets representing the edge components of Canny and Sobel edge images respectively. The number of Canny edge components in Canny edge image is $NC = \sum_{i=1}^{n} c_i$ and the number of Sobel edge components in Sobel edge image is $NC = \sum_{i=1}^{n} s_i$, where n is the number of edge component in the corresponding edge images. The rule is defined as

$$Rule = \begin{cases} BI, \quad if(NC < NS) \\ NBI, \quad Otherwise \end{cases} \tag{1}$$

where BI denotes a Blurred Image and NBI denotes a Non Blurred Image. This is illustrated in Figure 1 and 2. In Figure 1, (a) is NBI, (b) is gray image corresponding to the photo in (a), (c) is the result of Sobel edge operator before eliminating single pixel edge components (BEC), (d) is the result of Sobel edge operator after eliminating single pixel edge components (AEC), (e) is the result of Canny edge operator before eliminating single pixel edge components, and (f) is the result of Canny edge operator after eliminating single pixel edge components. It is noticed from Figure 1(c) and Figure 1(e) that the number of Sobel edge components in Figure 1(c) is more than the number of Canny edge components in Figure 1(e) for the image in Figure 1(a). It is also true from Figure 1(d) and Figure 1(f) as it satisfies the equation (1). Similarly, illustrations for BI are shown in Figure 2. In Figure2, (a) is the given BI, (b) is the gray image corresponding to photo in (a), (c) is the result of the Sobel edge operator before eliminating single pixel edge components, (d) is the result of the Sobel edge components after eliminating single pixel edge components, (e) is the result of the Canny edge operator before eliminating single pixel edge components and (f) is the result of the Canny edge operator after eliminating single pixel edge components. It is noticed from Figure 2(c) and Figure 2(e) that the number of Sobel edge components in Figure 2(c) is less than the number of Canny edge components in Figure 2(e) for the image in Figure 2(a). The same thing is true for Figure 2(d) and Figure 2(f) as they satisfy the equation (1).

The devised rule based metric as given in equation (1) works well because of the fact that the Canny edge detector has parameters that define the spatial frequencies of the filters and thus determine the behavior of the edge detector in case of blur [11]. On the other hand, it is not true in case of Sobel detector. In addition, we also believe that the efficient edge detector produces less number of edges compared to others detectors for good images. Hence, the proposed binary logic based rule metric classifies the blurred images successfully from the database of family album.



(a) RGB photo (b) Grey photo

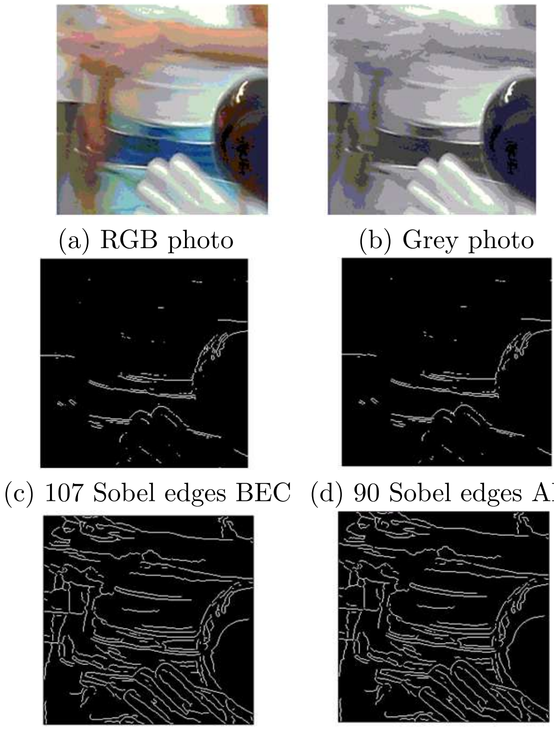
(c) 289 Sobel edges BEC (d) 246 Sobel edges AEC

(e) 180 Canny edges BEC (f) 174 Canny edges AEC

Fig.1: *Steps involved in deriving the rules for non blurred photo*

2.1 Heuristic Rules using Width of the Edge Components

In order to derive sophisticated rules, the proposed metric uses width of the edge components for classification of blurred photos. The width is estimated as the distance between the highest and lowest pixel locations of an edge in Y direction (MATLAB environment) for each edge in the Sobel and Canny edge images. Let $WS = ws1, ws2, \dots ws_n$ and $WC = wc_1, wc_2, \dots wc_n$ be the sets of widths computed for the edges in Sobel and Canny edge images respectively. The Mean for the set WS is computed as $MS = \frac{1}{n}\sum_{i=1}^{n} ws_i$, where n is the number of widths in the set WS. Similarly, the Mean for the set WC is computed as $MC = \frac{1}{n}\sum_{i=1}^{n} wc_i$, where n is the number of widths in the set WC. The metric counts the number of width edges (NS1) that are greater than or equal to Mean of the widths ($ifWS >= MS$). Similarly, the metric counts the number of width edges that are greater than or equal to Mean of the widths ($ifWC >= MC$). In the same way, the NS2 for the condition ($WS <= MS$) and NC2 for the condition ($WC <= MC$) are estimated.



(a) RGB photo (b) Grey photo

(c) 107 Sobel edges BEC (d) 90 Sobel edges AEC

(e) 147 Canny edges BEC (f) 139 Canny edges AEC

Fig.2: *Steps involved in deriving rules for blurred photos*

Rule 1 is defined as $\begin{cases} BI, & if(NC1 < NS1) \\ NBI, & Otherwise \end{cases}$

Rule 2 is defined as $\begin{cases} BI, & if(NC2 < NS2) \\ NBI, & Otherwise \end{cases}$

Rule 3 $\begin{cases} BI, & if(NC3 < NS3) \\ NBI, & Otherwise \end{cases}$ are derived,

where $NS3$ and $NC3$ are computed respectively for the conditions ($WS > MS$) and ($WC > MC$).

Rule 4 $\begin{cases} BI, & if(NC4 < NS4) \\ NBI, & Otherwise \end{cases}$ are derived,

where $NS4$ and $NC4$ are computed respectively for the conditions ($WS < MS$) and ($WC < MC$).

A total 4 rules are formed for the Mean parameter. In similar way, 4 rules are formed for the Median parameter computed using the widths array WS and WC. 4 more rules are formed for the Mode parameter. A total of 12 rules are derived. The same procedure is repeated for generating another set of 12 rules after eliminating single pixel edge components in the Sobel and Canny edge images. Hence total 24 rules are derived for classification of blurred photos from the family album database. The accuracy for all 24 rules is calculated to decide upon the best rule, which gives good accuracy for classification. The summary of the results is reported in Table 1, where highest accuracy obtained by the rule out of 8 (4 for BEC and 4 for AEC) rules corresponding to parameter is given. This procedure achieves 69.8% accuracy. To improve the accuracy, we have added few more rules, given in the next section.

2.2 Heuristic Rules using Sub Width of the Edge Components

To obtain a rule, which gives good accuracy for classification of blurred photos, the metric chooses sub width of edge components instead of just the width edge components, as described in section 2.1. The sub width is defined as the subset of the set WS and WC explained in the section 2.1. The subsets of width (SWS1) edges are the edges of WS that are greater than mean of the edges in the set $WS(if WS >= MS)$. Another subset (SWS2) is formed with width of edges in WS that are less than or equal to Mean of the edges in WS $(If WS <= MS)$. In the same way, the subsets say SWC1 and SWC2 are also obtained using WC and MC to derive the rules. As a result, for each set of width of edges (WS), the metric obtains two subsets of width edges ($SWS1$ and $SWS2$).
Similarly,

- the subsets SWS3 and SWS4 are obtained respectively using the conditions $(WS > MS)$ and $(WS < MS)$.
- the subsets SWC3 and SWC4 are obtained respectively using the conditions $(WC > MC)$ and $(WC < MC)$.

These are formed in order to obtain better rule for classification of blurred photos.

According to the procedure given in the section 2.1, the metric comprises of 8 (4 for BEC and 4 for AEC) rules for one set of edges for each parameter. But, in this procedure, the set of width edges is split into two subsets for each condition. Hence, the number of rules for each of the parameters increases to 16 instead of 8 (ref. section 2.1). Thus, the metric generates 48 (16 for Median and 16 for Mode parameters) rules for classification of blurred photos. The accuracy for all 48 rules is computed. The rule, which gives better accuracy out of the 16 rules for each of the parameter, is reported in Table 1.

3. EXPERIMENTAL RESULTS

We present here varieties of experimental results to evaluate the performance of the proposed metric in terms of accuracy and robustness. In this work, we have created our own database, which includes 89 blurred photos and 113 non-blurred photos, as there is no benchmark database for classification of blurred photos available in literature. The summary of the results of the rules corresponding to parameters is reported in Table 1, where the rule with sub width edges with mean gives better accuracy compared to other parameters. Accuracy is defined as the number of correctly classified photos divided by the total number of photos in the database. Besides accuracy, the corresponding rule is also given in Table 1. Hence the rules derived using sub width with mean parameter is used for classification of blurred photos in hierarchical way. For instance, 8 rules corresponding to the conditions (<= & >=) of sub width of edges with mean parameter are shown in Table 2, where D1 and D2 represent highest accuracy chosen among accuracies obtained by the different rules at different stages. It is also noticed from the Table 2 that 5th rule gives better accuracy comparing to accuracies of other 7 rules.

The sample results for 5th rule referring to Table 2 to classify the blurred photos is given in Figure 3, where we choose top 10 photos as sample blurred photos from the database for experimentation purpose. It is also observed from Figure 3 that the number of sub width Canny edge components is more than the number of sub width Sobel edge components for almost all photos. Hence, the proposed metric classifies the blurred photos successfully from the album database. Similarly, the sample results using 5th rule for classifying non blurred photos is given in Figure 4, where we have chosen top 10 photos from the non blurred photos database for experimentation purpose. It is noticed from Figure 5 that the number of sub width Canny edge components are lesser than the number of sub width Sobel edge components for almost all photos. This shows that the proposed metric classifies blurred photos from the family album database successfully. We also conducted experiments on rotated, scaled and noise photos to show that the proposed metric is robust to image rotation and scaling. The results are illustrated for both blurred photos and non blurred photos in Figure 5 and Figure 6 respectively. We notice from Figure 5 and Figure 6 that the proposed metric is invariant to rotation as it satisfies the equation (1) for different rotations. Similarly, we can also notice from Figure 7 and Figure 8 that the proposed metric is invariant to scaling as it satisfies the equation (1) for different scaled photos. But, however, it is noticed from Figure 9 and Figure 10 that the proposed metric is not invariant to noisy photo, as it does not satisfy the equation (1). Hence, the method is robust to rotation and scaling but not for noise.

Table 1: *Performance of the Proposed rules with different parameters*

Method	Parameters	Performance (%)	Rule (which gives maximum accuracy)
Width	Mean	69.8	<=&>=,AEC,<=
	Median	68.8	<=&>=,BEC,>
	Mode	59.9	<=&>=,AEC,<=
Sub Width	Mean	73.2	<=&>=,AEC,<=,<=
	Median	70.7	<=&>=,AEC,<=,>=
	Mode	56.9	<=&>=,BEC,<=,<=

Table 2: *Sample result of SubWidth Mean*

	<=&>=(%)							
	BEC				AEC			
	<=		>=		<=		>=	
	<=	>=	<=	>=	<=	>=	<=	>=
NBI(113)	79.6	63.7	52.2	30.9	64.6	48.6	36.2	22.1
BI(89)	34.8	60.6	76.4	87.6	84.2	60.6	93.2	94.3
Total(202)	59.9	62.3	62.8	55.9	73.2	53.9	61.3	53.9
D_1	62.8				73.2			
D_2	73.2							

Fig.3: *Proposed metric for top 10 Blurred photos*

Fig.4: *Proposed metric for top 10 Non Blurred photos*

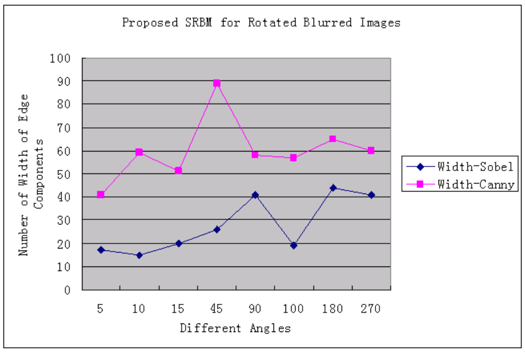


Fig.5: *Proposed metric for rotated Blurred photo (Figure 2 (a))*

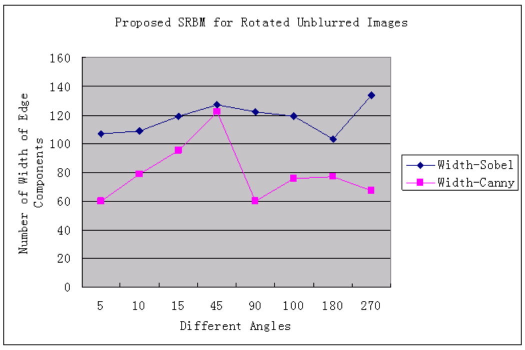


Fig.6: *Proposed metric for rotated Non Blurred photos (Figure 1 (a))*

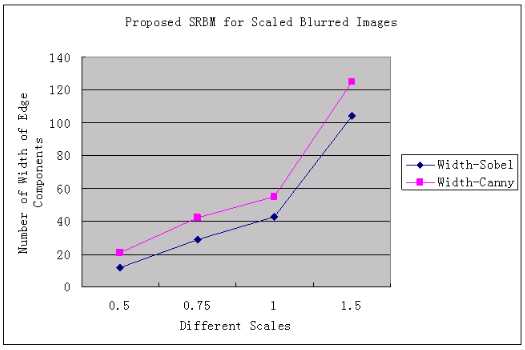


Fig.7: *Proposed metric for scaled Blurred photos (Figure 2(a))*

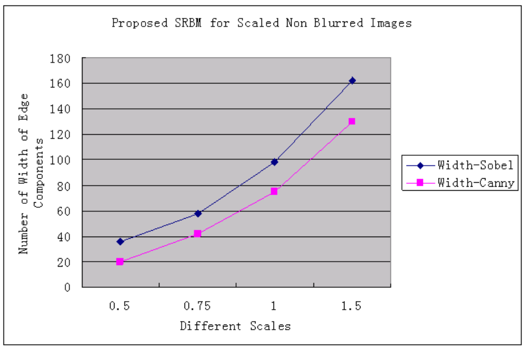


Fig.8: *Proposed metric for scaled Non Blurred photos (Figure 1 (a))*

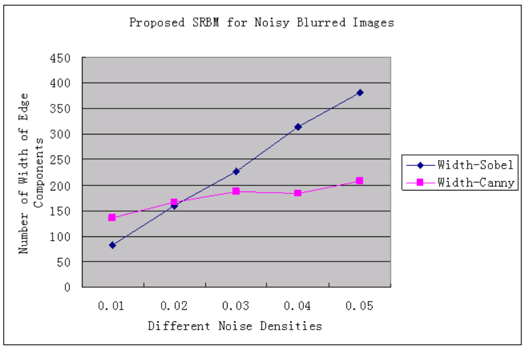


Fig.9: *Proposed metric for noisy Blurred photos Figure 2(a))*

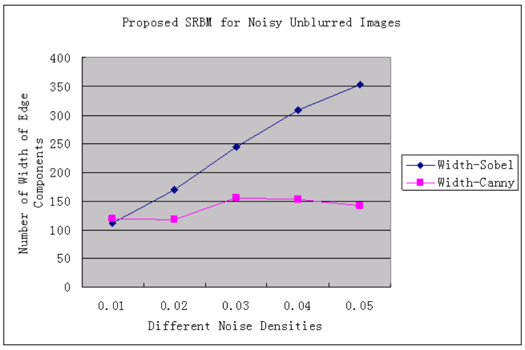


Fig.10: *Proposed metric for noisy Non Blurred photos (Figure 1 (a))*

4. COMPARATIVE STUDY

We evaluate the performance of the proposed metric with the results of the existing methods given in [4] and [6] in terms of suitability for automatic classification of blurred photos from the family album database. The performance of the existing methods is illustrated in Figure 11 and 12 respectively for both blurred photos and non blurred photos. The sample results of the existing method [6] for top 10 blurred photos and non blurred photos from the database is shown in Figure 11, where it is noticed that the values of metrics for blurred and non blurred photos are overlapping each other. Hence, it is impossible to classify the blurred photo with the metric values. The sample results of the existing method [4] for top 10 blurred photos and non blurred photos from the database is shown in Figure 12, where it is noticed that the values of metrics for blurred and non blurred photos are overlapping each other. Hence, it is impossible to classify the blurred photos with the metric values. However, the existing methods are good for measuring degree of blurrness with the help of human intervention and the use of proper threshold. The main reason for not classifying blurred photos successfully is that the existing methods depend on the Sobel edges. However, as blur increases the number of Sobel edges decreases because sharpness decreases as blur increases. This is seen in Figure 13, where the values of Sobel and Canny edge operators change randomly for different blur density levels. Hence, the existing metrics are not suitable for classification of blurred photos from the database of family album. But, developing good edge detector for blurred photos is still an elusive goal for researchers. The overall performance of the proposed and existing methods with different parameters is given in Table 3, it is evident that the proposed metric outperforms the existing methods in terms of classification of blurred photos without any priori knowledge and considered robustness.

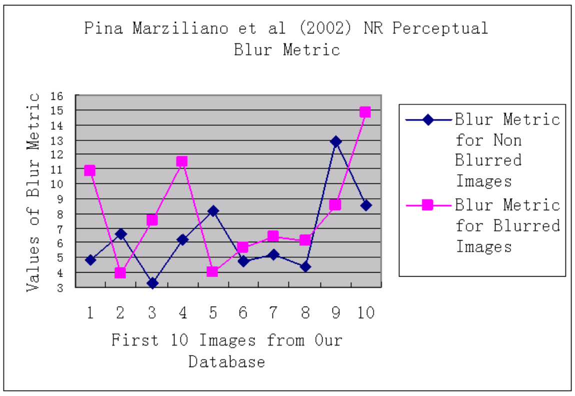


Fig.11: *Performance of the existing blur metric [6] for classification of blurred photos*

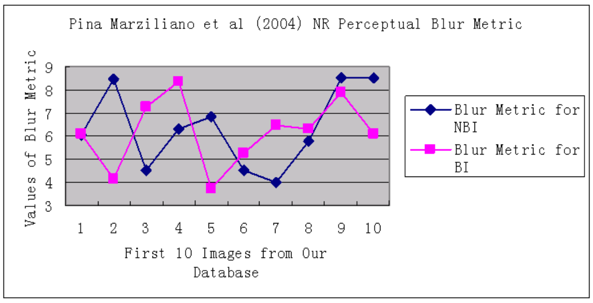


Fig.12: *Performance of the existing blur metric [4] for classification of blurred photos*

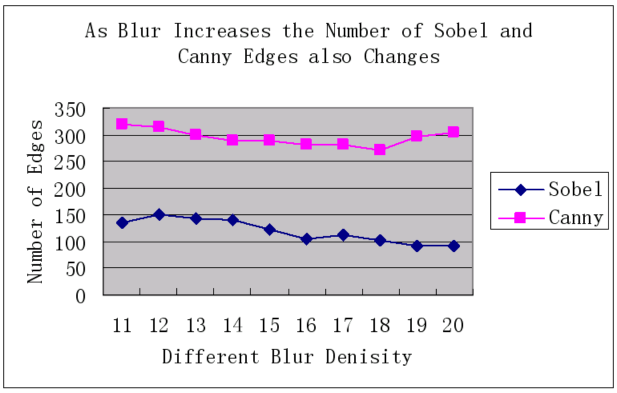


Fig.13: *The effect of blur on Sobel and Canny edge detectors*

5. DISCUSSION

We present discussion on the results of the proposed method in terms of classification of blurred and non blurred photos. To classify the blurred and non blurred photos, the generated rules (refer to Table 2) are used in hierarchical manner. The classification results using these 5 rules (chosen from Table 2) are represented in the form of decision tree and shown in Figure 14, where the number in the left node denotes the correct classification and the number in right node denotes the wrong classification. It is noticed from Figure 14 that the 5th rule applied at fist level in the decision tree, classifies 75 photos as blurred photos correctly out of 89 and 73 photos as non-blurred photos out of 113. Similarly, the rule 1 (refer to Table 1) at second level in decision tee classifies single photo as blurred photo correctly out of 14 and 18 photos as non blurred photos correctly out of 40.

• The rule 2 applied at third level in decision tree classifies 3 photos as blurred photos correctly and 5 photos as non blurred photos correctly out of 22.

• The rule 3 applied at fourth level in decision tree does not classify blurred photos but it classifies 1 photo as non blurred photos correctly out of 17.

• The rule 4 applied at fifth level in decision tree classifies 6 photos as blurred photos correctly out of 10 and 1 photo as non blurred photo correctly out of 16.

• The rule 8 applied at sixth level in decision tree classifies 3 out of 4 photos as blurred correctly and 1 out of 15 photos as non blurred correctly.

Total 88 out of 89 photos are classified as blurred correctly and 99 out of 113 photos are classified as non blurred photos correctly with 6 levels. Thus, a total of 187 photos are classified out of 202 photos with 6 rules. Hence, the classification accuracy is 92.5%. The unclassified blurred and non-blurred photos are given in Figure 15 and Figure 16 respectively. It is realized that the reason for misclassification is presence of more number of faces in the photos. It is observed that the number of edges differs from one edge detector to another edge detector, when faces are present in the photos. It is noted that we use only one method with 6 rules to classify the 202 photos out of 48 rules. Thus, even the size of the database increases, it does not make much difference in classification. This is the advantage of the proposed method.

6. CONCLUSION

In this paper, we have made an attempt to solve new problem of classification of blurred photos without having any a priori knowledge of the original photo. We have proposed a new rule based boolean blur metric to classify the blurred photos from the family album database in terms of width of Sobel and Canny edge components and the statistical parameters such as mean, median and mode. It is shown that the devised metric is content independent and

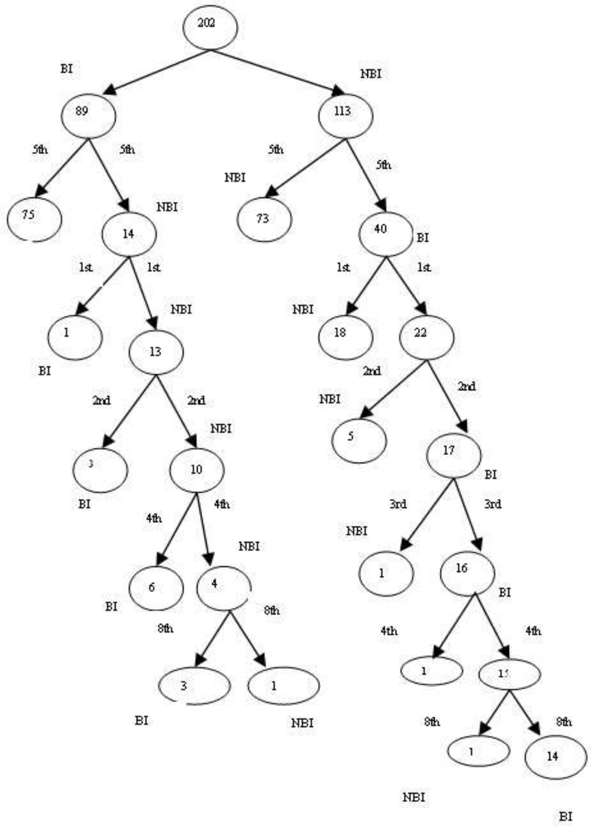


Fig.14: Decision tree for classification of Blurred photos and Non Blurred photos using sub width edges with Mean parameter

Fig.15: Unsuccessful blurred photo

Fig.16: Unsuccessful Non Blurred photos

Table 3: *Overall summary of the proposed and existing methods with respect to classification of blurred photos*

Methods	Different Parameters								
	Human Intervention	Ideal Information	Complexit	Applications	Parametric/ NonParametric	Subjective Test	Invariance Property	Noise	Classification
Deblurring	Yes to decide deblurring parameters	Yes	More	Satellite and Compressed images	Parametric	Yes	No	Yes	Not suitable
FR	Yes	Yes	Less	Compressed images	Parametric	Yes	No	No	Not suitable
RR	Yes	Yes	Less	Compressed images	Parametric	Yes	No	No	Not suitable
HIQM	Yes	No	More	Compressed images	Parametric	Yes	No	No	Not suitable
Pina Marziliano et al (2002)	No	No	Less	Compressed images	Parametric	Yes	No	No	Not suitable
Pina Marziliano et al (2004)	No	No	Less	Compressed images	Parametric	Yes	No	No	Not suitable
Proposed (RBM	No	No	Less	Motion blur by digital camera	Non parametric	No	Yes	No	Suitable

unsupervised. Based on experimental results, it is also shown that the existing blur metrics are not suitable for automatic classification of blurred photos. Furthermore, the proposed metric is invariant to rotation and scaling but it is sensitive to noise. The metric can be extended to video images since the method has low complexity. It may be easy to adopt this method in digital camera because of simplicity and it does not involve any expensive computations. It can also be used as a validation technique for deblurred images for some extent.

7. ACKNOWLEDGEMENT

The authors express sincere gratefulness to Prof. Mohan S. Kankanhalli, Department of Computer Science, National University of Singapore, Singapore for his useful suggestions to improve the quality of the paper. We also thank Dr. Pradeep for providing data set for experimentation. Finally, we must thank the reviewers for their critical observations about the method.

References

[1] Moshe Ben-Ezra and Shree K. Nayar, "Motion-Based Motion Deblurring", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 26, No. 6,pp 689-698, June 2004.

[2] Ziya Telatar, "Adaptive filter design for image deblurring by using multi-criteria blurred image information", *Digital Signal Processing*, 15,pp 4-18, 2005.

[3] Tubagus Maulana Kusuma, Hans-Jurgen Zepernick and Manora Caldera, "On the Development of Reduced-Reference Perceptual Image Quality Metric", *Proceedings of the 2005 Systems Communications (ICW 05)*,2005.

[4] Pina Marziliano, Frederic Dufaux, Stefan Winkler and Touradj Ebrahimi, "Perceptual blur and ringing metrics: application to JPEG2000", *Signal Processing: Image Communication 19*, pp 163-172, 2004.

[5] Tubagus Maulana Kusuma and Hans-Jurgen Zepernick, "A Reduced-Reference Perceptual Quality Metric for In-Service Image Quality Assessment", *Joint Workshop on Mobile Future and Symposium on Trends in Communication Sympotic 03*, 26-28, , pp 71-74, October 2003.

[6] P. Marziliano, F. Dufaux, S. Winkler and T. Ebrahimi, "A no-reference perceptual blur metric", *Proceedings of the International Conference on Image Processing*, Vol. 3, Rochester, NY, pp 57-60, 2002.

[7] Timothy K. Shih, Rong-Chi Chang and Yu-Ping Chen, "Motion Picture Inpainting in Aged Films", *ACM Multimedia 05*, November, Singapore, 6-11, pp 319-322, 2005.

[8] James H. Elder and Steven W. Zucker, "Local Scale Control for Edge Detection and Blur Estimation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 7, July 1998.

[9] Amlan Kundu, "Robust edge Detection", *Pattern Recognition*, Vol. 23, No. 5, pp 423-440, 1990.

[10] D.S Guru, B.H Shekar and P. Nagabhushan, "A simple and robust line detection algorithm based on small eigenvalue analysis," *Pattern Recognition Letters 25*, pp 1-13, 2004.

[11] J, F Canny, "A Computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8(6): 679698, Nov 1986.

P. Shivakumara received B.Sc., M.Sc., M.Sc Technology by research and Ph.D degrees from the University of Mysore, Mysore, Karnataka, India in 1995, 1999, 2001 and 2005, all in computer science. In addition to this, he has obtained educational degree (B.Ed) from Bangalore University, Bangalore, Karnataka in 1996.
From 1999 to 2005, he was Project Associate at the University of Mysore, where he obtained M.Sc Technology by research degree and Ph.D degree in computer science and he conducted research on pattern recognition, image processing, document image processing, document image mosaicing, character recognition, skew detection, face detection and face recognition. He also worked as a Research Fellow with Prof. Mohan S Kanakanhalli in the field of image processing and multimedia at Department

of Computer Science, National University of Singapore, Singapore from 2005-2007. He worked as Research Consultant at Nanyang Technological University, Singapore for the period of 6 months. Based on this work he has published around 90 research papers in national, international conferences and journals. He has been reviewer for several conferences and journals. Currently, he is working at National University of Singapore (NUS) as a Research Fellow in the field of image processing and pattern recognition under the supervision of Prof. Chew Lim Tan, Department of Computer Science, National University of Singapore, Singapore. His research interests are in the area of image processing, pattern recognition, text extraction from video, document image processing, biometric applications and automatic writer identification.

Basavaraj S. Anami has received B.E in Electrical Engineering from Karnataka University Dharwad, M. Tech in Computer Science from IIT Madras, PhD from University of Mysore, Mysore, India, during 1981,1986 and 2002 respectively. I has been serving as professor and Head of Department of Computer Science, Basaveshwar Engineering College, Bagalkot, India. He has teaching experience of 27 years including undergraduate and graduate programmes. He has authored a book on Computer Fundamentals and C Programming, published by Prentice Hall of India, New Delhi. He has served as visiting professor during 2006 Fall at Saginaw Valley State University, Midland, USA. He has around 75 research papers published at National and Inter National levels. His research areas include Image Processing, Artificial Intelligence, Regional Language Processing and Non-Speech signal processing.

G. Hemantha Kumar graduated from Department of Computer Science at the University of Mysore, India in 1988. He joined the University as a lecturer in the same year. He worked as Reader in the same Department from 1988 to 2007 and currently he is serving as Professor and Chairman for the Department of Computer Science. His research focuses on Pattern Recognition and Image Processing. His current area of research includes Document Analysis and Biometric including Face and Speech recognition.