Automatic Vehicle Number Plate Recognition And Human Detection

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Abstract- *Human detection and tracking have been an extremely active area over the past decade. The importance of this area arises from its numerous applications such as smart vehicles, military applications and security system. The proposed method presents a real-time system for detecting and tracking humans from fast moving vehicles. This also presents a simpler and faster variant of the popular Superpixel segmentation algorithm for human detector. This also performs convolution operation of Riesz fractional derivative over each input image by enhancing the edge strength in it.*

Keywords- Low quality images, Enhancement model, Riesz fractional order derivative, License plate recognition,, Human detection, SLIC algorithm.

I. INTRODUCTION

Automatic license Plate Recognition (LPR) without human intervention or influence is of great importance in the field of image processing and pattern recognition. This is because LPR plays a vital role in numerous applications especially in real time environments, such as toll collection of expressway, surveillance and management systems of unattended parking lots, traffic control, and customs control [1]. In addition, license plate recognition is used in control systems for areas with limited accessibility, such as embassies, factories, army barracks, elite city quarters and for identifying lost or stolen vehicles [2]. Since LPR is required by real time applications as mentioned above, high detection and recognition rates are necessary to meet the requirement of such real time applications. Though two decades have been spent for improving LPR systems according to situations, there are still several challenges in achieving high detection and recognition rates [3-7]. One such factor is low quality affected by the following reasons [1]: (i) severe outdoor illumination conditions during image acquisition, where we can expect effects from headlight and sunlight, (ii) Low quality license plate images which often include damaged or stained license plates and non-license plate characters printed on vehicles, and Perspective distortions which are quite common due to distance or viewpoint variations. It is evident from the illustration provided in Fig. 1, where the text detection method in [8] that uses stroke width transforms for text detection in natural scene images, fails to detect complete license plate numbers for the low quality image (low contrast) shown in Fig. 1(a), while the same method detects complete license plate numbers for the enhanced image given by the proposed model. Furthermore, it is also observed from Fig. 1(a) that the text detection method in [8] produces false positives for low quality images before enhancement; however, fewer false positives/no false positives are produced for the enhanced image. It is true that text detection results do not provide complete information in all the time due to background influence. When we give incomplete text detection results as the input for a binarization method, there will be much more loss of information during binarization. Therefore, we can conclude that the enhancement improves text detection and recognition results significantly. On the other hand, we can also infer that there is an urgent need for developing a generalized model for enhancing license plate images, which should withstand the above mentioned causes to improve the quality of these images. Consumers, as human beings, take vast numbers of photographs of people. A prime example is the selfie, which is an instantaneous self-portrait usually captured with smart phones or digital cameras. The selfie has now become commonplace. Many applications and tools such as sticks, tripods, and even drones for better selfies prove its significant popularity. Arguably, the person category is among the most frequently captured and therefore important photographic subject. The main objective of this paper is to human segmentation based on non parametric learning.

II. PROPOSED MODEL

The proposed method uses a non parametric learning human segmentation based on support vector machine. To exploit the spatial characteristics of training human instances, the proposed framework learns as many region-wise SVM models as the number of superpixels. Conventional methods are evaluated on neatly captured iconic images, but natural scenes in a real-world photograph are very complicated. Natural photographs usually contain cluttered background and large illumination variations. The existing methods are mainly resorting to a single optimization formulation with simple color models. Human segmentation is basically a complex problem of labelling a large number of pixels in different parts of the complicated image. In this complex segmentation task, choosing a simple modeling could produce an unwanted result. The surveillance camera is usually designed for capturing a big scene that includes a whole vehicle, therefore the license plate only occupies a small region of the whole image. This leads to insufficient details for kernel estimation. Due to the fast motion, the size of the blur kernel is very large.

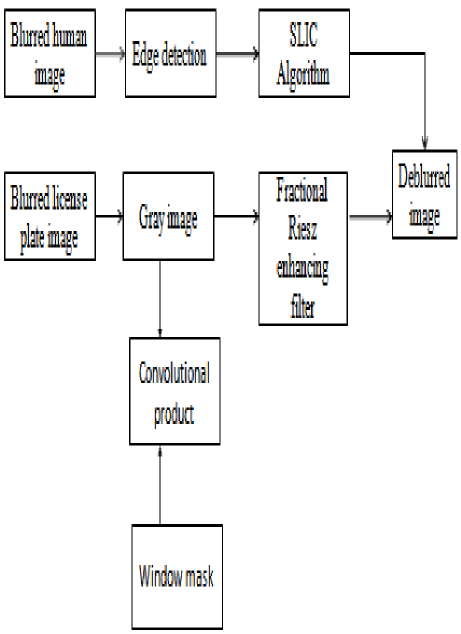

Fig 1: BLOCK DIAGRAM

1) Input image

The proposed model involves differential operation by performing convolution operation over each input image with the Riesz fractional derivative window; it enhances edges irrespective of distortions created by multiple factors. On license plate detection, recognition and contrast enhancement that most of the methods directly and indirectly use the baseline enhancement techniques as preprocessing steps to improve the quality of input images. Therefore, in this work, we implement the same baseline enhancement techniques to give fair comparative studies with the proposed model in terms of quality metrics. PSNR is calculated by the mean squared error between corresponding pixel values of the enhanced image and the input image.

2) Gray level Conversion

In first step the input color image is converted into grayscale image. The grayscale image has represented by luminance using 8 bits value. The luminance of a pixel value of a grayscale image ranges from 0 to 255. The conversion of a color image into a grayscale image is converting the RGB values (24 bit) into grayscale value (8 bit). Riesz Fractional derivative nonlinearly preserves both edge features in image regions where the gray level changes extensively, and texture features in other regions where the gray level does not changes extensively. The logic behind applying fractional Riesz for image enhancement is that the enhancement of an image is determined at each pixel, which enhances low-frequency details in the regions where gray-level changes are insignificant.

3) Pre processing

The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. It proposed based on edge density as preprocessing steps for improving license plate detection. However, edge density is sensitive to complex background and low contrast images. All the existing methods propose license plate detection as a preprocessing step for recognition, the reference is same for both license plate detection and recognition. It is noted from the literature review on license plate detection, recognition and contrast enhancement that most of the methods directly and indirectly use the baseline enhancement techniques as preprocessing steps to improve the quality of input images.

4) Riesz Fractional Differential Mask

Riesz Fractional derivative nonlinearly preserves both edge features in image regions where the gray level changes extensively, and texture features in other regions where the gray level does not changes extensively. The proposed Riesz Fractional derivative model is conducted from the improved. Riesz fractional approach the starting point is to consider the Riesz fractional operation as follows.

$$\mathrm{R}^{\varphi} = \emptyset(t) = \frac{1}{2\sin\left(\frac{\alpha\pi}{2}\right)\Gamma(1-\alpha)}\left(\frac{d}{dt}\right)\int_{-\infty}^{\infty}(t-s)^{(1-\alpha)}\,\emptyset(s)\,ds$$

Where Γ is the gamma function, and α is the fractional power order. Riesz fractional derivative is approximated with step *h* is as follows: Our image enhancement model is based on the discrete form of Riesz fractional differential operator when $0 < \alpha < 1$. Equation (3) applies uniformly in the whole image $I(\nu, \lambda)$ with respect to two variables ν and λ. In this work, we implement Riesz fractional derivative mask along eight different directions, namely, positive ν -axis, negative ν -axis, positive λ –axis, negative λ - axis, diagonal - right upward, diagonal - left downward, diagonal - right downward, and diagonal - left upward, respectively.

In this work, we implement Riesz fractional derivative mask along eight different directions, namely, positive ν -axis, negative ν -axis, positive λ –axis, negative λ -axis, diagonal - right upward, diagonal - left downward, diagonal - right downward, and diagonal - left upward, respectively. Now, we have the following forms of the approximation of the fractional centered difference of Riesz fractional partial differential on positive *v*-axis and positive λ-axis, respectively:

$$\lim_{h\to 0}\left(\frac{\Delta_h^{\alpha} I(v,\lambda)}{1+n}\right)^{*} \approx \lim_{h\to 0} 2/h^{\alpha}\sum_{n=0}^{\infty}\frac{(-1)^n}{\alpha\,\Gamma\left(\frac{\alpha}{2}-n+1\right)\Gamma\left(\frac{\alpha}{2}+n+1\right)} I(v - nh, \lambda)$$

.

which yields the following coefficients of Riesz Fractional derivative of order α:

$$w_0 = \frac{2\Gamma(\alpha+1)}{\Gamma(\frac{\alpha}{2}+1)^2},$$

$$w_1 = \frac{(-2)\Gamma((\alpha+1)}{\Gamma(\frac{\alpha}{2})+1)^2(\frac{\alpha}{2}+1)}$$

5) License Plate Detection and Recognition

This proposed method is robust for text detection in natural scene images. This method involves Maximally Stable Extremal Regions concept (MSER) which is used for character candidate detection, a classifier at character level for text removing false text candidates and finally grouping character into text lines. This method involves Maximally Stable Extremal Regions concept (MSER) which is used for character candidate detection, a classifier at character level for text removing false text candidates and finally grouping character into text lines. However, the scope of this method is limited to text detection but not license plate detection, where one can expect numerals with alphabets. In addition, these images are usually affected by severe illumination, light illumination, blur due to vehicle movement, Gradient vector flow, Stroke width distance, Symmetry features, License plate recognition and images capturing at different angles. As a result, the method in does not work well for license plate images. Therefore, we propose modifications to MSER by adding stroke width information and a classifier such that the modified method works well for license plate images. In case of license plate images, stroke width distance is constant for all characters including numerals in images. This is valid because license plate images use upper case letters and numerals but not lower case letters. Therefore, MSER with stroke width information is robust to license plate images.

6. Simple Linear Iterative Clustering Algorithm

A cluster of connected pixels with similar features (ex: color, brightness, Texture...).It can be regarded as a result of over segmentation. Superpixels are becoming increasingly popular for use in computer vision applications. However, there are few algorithms that output a desired number of regular, compact superpixels with a low computational overhead. We introduce a novel algorithm that clusters pixels in the combined five-dimensional color and image plane space to efficiently generate compact, nearly uniform superpixels. The simplicity of our approach makes it extremely easy to use a lone parameter specifies the number of superpixels and the efficiency of the algorithm makes it very practical. Experiments show that our approach produces superpixels at a lower computational cost while achieving a segmentation quality equal to or greater than four state-of-the-art methods, as measured by boundary recall and under-segmentation error. We also demonstrate the benefits of our superpixel approach in contrast to existing methods for two tasks in which superpixels have already been shown to increase performance over pixel-based methods. Superpixels provide a convenient primitive from which to compute local image features. They capture redundancy in the image and greatly reduce the complexity of subsequent image processing tasks.

IV. RESULT AND DISCUSSION

Deconvolution is a computationally intensive image processing technique that is being increasingly utilized for improving the contrast and resolution of digital images. De-blurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur.

SLIC is a simple and efficient method to decompose an image in visually homogeneous regions. It is based on a spatially localized version of k-means clustering. Similar to mean shift or quick shift, each pixel is associated to a feature vector.

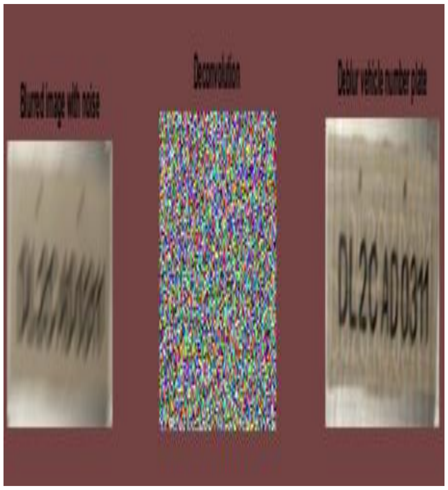

Fig 2:Deblur License Plate Image

Fig 3:Deblur Human Image

V. CONCLUSION AND FUTURE WORK

This paper proposed a superpixel-based non-parametric framework that achieves high-quality human segmentation. The proposed scalable framework employs various features of superpixels including surrounding edges, color distribution model. Furthermore, the framework automatically captures the intrinsic spatial characteristics of the human shape, by performing feature learning and prediction on each grid of the 2D model array. In future work, we will apply the proposed framework to other various object categories.

REFERENCES

[1] Y.-W. Tai, H. Du, M. Brown, and S. Lin, "Correction of spatially varying image and video motion blur using a hybrid camera," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 32, no. 6, pp. 1012–1028, Jun 2010.

[2] W. Zhou, H. Li, Y. Lu, and Q. Tian, "Principal visual word discovery for automatic license plate detection," IEEE Transactions on Image Processing (TIP), vol. 21, no. 9, pp. 4269–4279, 2012.

[3] W. Zhou, Y. Lu, H. Li, Y. Song, and Q. Tian, "Spatial coding for large scale partial-duplicate web image search," in Proceedings of the 18th ACM international conference on Multimedia, Oct 2010, pp. 511–520.

[4] W. Zhou, H. Li, R. Hong, Y. Lu, and Q. Tian, "Bsift: toward data independent codebook for large scale image search," IEEE Transactions
on Image Processing (TIP), vol. 24, no. 3, pp. 967–979, 201

[5] W. Zhou, M. Yang, H. Li, X. Wang, Y. Lin, and Q. Tian, "Towards codebook-free: Scalable cascaded hashing for mobile image search," IEEE Transactions on Multimedia (TMM), vol. 16, no. 3, pp. 601–611, 2014.

[6] S. Cho and S. Lee, "Fast motion deblurring," ACM Transactions on Graphics (TOG), vol. 28, no. 5, pp. 145:1–145:8, Dec 2009.

[7] Q. Shan, J. Jia, and A. Agarwala, "High-quality motion deblurring from a single image," ACM Transactions on Graphics (TOG), vol. 27, no. 3, pp. 73:1–73:10, 2008.

[8] L. Xu, S. Zheng, and J. Jia, "Unnatural ℓ0 sparse representation for natural image deblurring," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun 2013, pp. 1107– 1114.

[9] H. Cho, J. Wang, and S. Lee, "Text image deblurring using text-specific properties," in Proceedings of European Conference on Computer Vision(ECCV), Oct 2012, pp. 524–537.

[10] L. Xu and J. Jia, "Two-phase kernel estimation for robust motion deblurring," in Proceedings of European Conference on Computer Vision(ECCV), Sep 2010, pp. 157–170.

[11] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, "Understanding blind deconvolution algorithms," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 33, no. 12, pp. 2354–2367, 2011.

[12] J. Oliveira, M. Figueiredo, and J. Bioucas-Dias, "Parametric blur estimation for blind restoration of natural images: linear motion and outof- focus," IEEE Transactions on Image Processing (TIP), vol. 23, no. 1,

[13] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," ACM Transactions on Graphics (TOG), vol. 25, no. 3, pp. 787–794, 2006.

[14] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman,"Removing camera shake from a single photograph," ACM Transactions on Graphics (TOG), vol. 25, no. 3, pp. 787–794, 2006.

[15] C. Wang, Y. Yue, F. Dong, Y. Tao, X. Ma, G. Clapworthy, H. Lin,and X. Ye, "Non edge-specific adaptive scheme for highly robust blind motion deblurring of natural images," IEEE Transactions on Image Processing (TIP), vol. 22, no. 3, pp. 884–897, Mar 2013.

[16] R. Hartley and A. Zisserman, Multiple View Geometry in Computer Vision, 2nd ed. Cambridge University Press, 2004.

[17] J.-F. Cai, H. Ji, C. Liu, and Z. Shen, “Blind motion deblurring from a single image using sparse approximation,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun2009, pp. 104–111.

[18] J. F. Cai, H. Ji, C. Liu, and Z. Shen, “Framelet-based blind motion deblurring from a single image,” IEEE Transactions on Image Processing(TIP), vol. 21, no. 2, pp. 562–572, Feb 2012.

[19] S. Dai and Y. Wu, “Motion from blur,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun2008, pp. 1–8.

[20] Q. Shan, W. Xiong, and J. Jia, “Rotational motion deblurring of arigid object from a single image,” in Proceedings of IEEE International Conference on Computer Vision (ICCV), Oct 2007, pp. 1–8.

[21] J. Wright, A. Yang, A. Ganesh, S. Sastry, and Y. Ma, “Robust face recognition via sparse representation,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 31, no. 2, pp. 210–227, 2009.

[22] M. Elad and M. Aharon, “Image denoising via sparse and redundant representations over learned dictionaries,” IEEE Transactions on Image Processing (TIP), vol. 15, no. 12, pp. 3736–3745, Dec 2006.

[23] Z. Hu, J.-B. Huang, and M.-H. Yang, “Single image deblurring with adaptive dictionary learning,” in Proceedings of IEEE International Conference on Image Processing (ICIP), Sep 2010, pp. 1169–1172.

[24] X. Chen, X. He, J. Yang, and Q. Wu, “An effective document image deblurring algorithm,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun 2011, pp. 369–376.

[25] B. Epshtein, E. Ofek, and Y. Wexler, “Detecting text in natural scenes with stroke width transform,” in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun 2010, pp. 2963–2970.

[26] J. Mao, H. Li, W. Zhou, S. Yan, and Q. Tian, “Scale based region growing for scene text detection,” in Proceedings of the 21st ACM international conference on Multimedia, Oct 2013, pp. 1007–1016.

[27] A. Goldstein and R. Fattal, “Blur-kernel estimation from spectral irregularities,” in Proceedings of European Conference on Computer Vision(ECCV), Oct 2012, pp. 622–635.

[28] G. Liu, S. Chang, and Y. Ma, “Blind image deblurring using spectral properties of convolution operators,” IEEE Transactions on Image Processing(TIP), vol. 23, no. 12, pp. 5047–5056, Dec 2014.

[29] H. Zhang, D. Wipf, and Y. Zhang, “Multi-observation blind deconvolution with an adaptive sparse prior,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 36, no. 8, pp. 1628–1643, Aug 2014.

[30] L. Yuan, J. Sun, L. Quan, and H.-Y. Shum, “Image deblurring with blurred/noisy image pairs,” ACM Transactions on Graphics (TOG),vol. 26, no. 3, Jul 2007.

[31] X. Zhu, F. ˇSroubek, and P. Milanfar, “Deconvolving PSFs for a better motion deblurring using multiple images,” in Proceedings of European Conference on Computer Vision (ECCV), Sep 2012, pp. 636–647.