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Rule-Based Optical Character Recognition for Serial Number on Renminbi Banknote

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Abstract

A rule-based optical character recognition system for the recognition of serial number on Renminbi (RMB) banknote is presented. It is based on the observation that the characters, including English letters and numbers, can be classified using two hand-crafted features, which are the opening and the loop. Each character has certain characteristics in terms of those two features and classification is achieved following the proposed scheme. The proposed system has been tested on 2245 RMB bills, which contain 22313 characters, and accomplished 99.35% for horizontal characters and 99.84% for vertical characters under 30ms processing time per banknote.

Keyword: Optical character recognition software, Serial number recognition, Text recognition, Feature extraction, Character recognition

1. Introduction

With the advance of computer vision, manpower is gradually replaced by automation equipment for inspecting the objects, recognizing patterns and other repetitive tasks. Among all the computer vision techniques, optical character recognition (OCR) is a field that attracts enormous research interests because of its difficulty and because of its application in laborious tasks, such as recognizing product serial number, invoices number, car plates and documents. Different kinds of OCR system have been developed to suit various applications and for the variety of characters, including the deformed, the cluttered, the stained, etc.

Our research focuses on characters recognition for serial number on Renminbi (RMB) banknote, which is one of the top five currencies in the world. In banking industry, each bill has a unique serial number, which is designed to prevent counterfeiting, to manage the tracking of the missing bills and to provide information of the bill. Despite the importance of serial number, the task related to sorting and processing through all kinds of bills can be troublesome. Instead of manually working through all of the bills, OCR is considered because of its accuracy and quickness. However, a matured OCR system incorporated with a bill counter, which is available to precisely count the quantity of banknotes, is not maturely developed. Therefore, our system aims to develop an OCR system that can fully integrate with the bill counter.

The accuracy of recognizing the serial number on the bill depends on various factors, such as the release version, the font, and the denomination. Due to those abovementioned factors, the location of printed serial number, which is the region of interest (ROI), will be different. As a result, an accurate OCR system along with effective and efficient ROI detection is proposed in this paper.

2. Previous work

Optical character recognition has been an interesting research topic for more than fifty years. Its domain-specific applications have different limitations and require different kinds of methods. As a result, many schemes have been proposed and those approaches can be broadly categorized into two groups, (I) classification with handcrafted features and (II) deep learning methods.

Traditionally, OCR systems are (I) handcrafted methods, which contain several tuned and pipelined modules. The modules are inclusive of data preprocessing, character segmentation, feature extraction and character recognition. Data preprocessing module, which contains data collecting, binary thresholding and noise elimination, is usually task specific and different methods are considered according to different types of data. Moreover, skew angle calibration [1] is used to align and rectify the characters to horizontal and vertical direction if the character is rotated.

After data preprocessing, the region of interest (ROI) in the entire images is specified. Character segmentation module then splits the characters apart from the background and from each other. While most methods [2] extract the features by segmenting the character into grids, [4] uses hexagonal cells to separate characters. Connected component is also common method [5-9] for the estimation of the boundary of each character. Another method is X-Y-Tree decomposition [1], which solves the segmentation problem from the graphics viewpoints.

Utilizing features is the simplest and also significant way to represent a character. For feature extraction, histogram of gradient (HOG) is a feature descriptor that detects the orientation of gradients. Gradient orientation of each character is described with HOG in [10-12]. Other feature descriptors, such as contour gradients, contour ratios and centroid-to-boundary distances [1], are also utilized to extract useful features. These features might be combined as mentioned in [18], which uses A*-like algorithm to dynamically determine the combination of feature vectors.

Character classification is the procedure to determine category of a character. Machine learning techniques are usually applied in this procedure and these techniques can be categorized into unsupervised methods and supervised methods. Unsupervised algorithms, such as K-Nearest Neighbors (KNN) [2-3], need not the label of character to train the data. Instead, the aggregation characteristic of same character in feature space is used to cluster the data. Different from unsupervised learning algorithms, supervised algorithm needs the label of character to train a classifier to decide the category of an input character. Such algorithms include support vector machines (SVM) [13-14] and adaptive boosting (AdaBoost) [15].

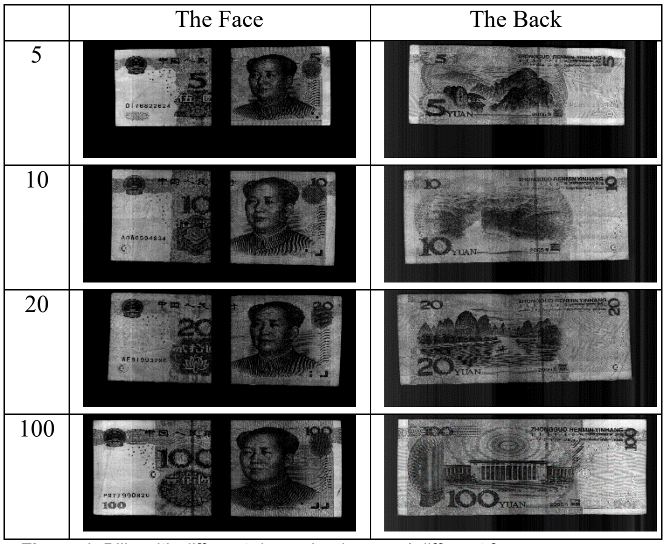


Figure 1. Bills with different denominations and different faces.

Figure 2. Flow-chart of the proposed system.

Figure 3. A skewed banknote in the scanned image.

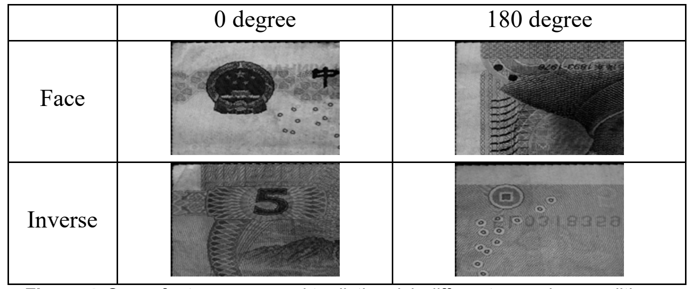


Figure 4. Some features are used to distinguish different scanning conditions.

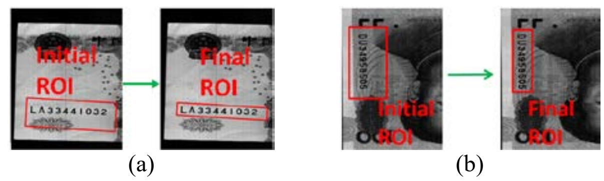


Figure 5. Serial number ROI. (a) Horizontal (b) Vertical

The modern approach of OCR is (II) deep learning. Deep learning is constructed with multiple layers, including convolution layer, rectified linear unit and pooling layer. Such approach projects the character into a high dimension space and the neurons will decide the features to be extracted and the learning algorithms. The advantage of this approach is its generalization, indicating that once the classifiers is trained and obtained, it can be used in multiple applications, such as handwritten character classification [16] and street view number recognition [17]. However, it is highly computational exhaustive and need the hardware, like GPUs, to speed up the entire process. Deep learning approach is not considered as one of our solutions because of the hardware and the price limitation.

Our proposed method falls into the first category of approaches regardless of the character classification part. No training is needed for the classification purpose in our system and some rules based on observation are designed to replace the classifier. Rule-based method in our system surpasses other classifiers in terms of computational speed and memory usage, which are the two chief constraints in our application.

3. System overview

The proposed system is an optical character recognition system, which is mainly designed for RMB banknote serial number. The proposed system is implemented on the Blackfin Dual Core ADSP-BF609 Embedded Processor, which has less than 8 MB memory. Hence, our system takes the limited computation space and precision into consideration.

The input of our system is a scanned bill on a black background as shown in Figure 1. The scanning machine is a charge-coupled device (CCD) along with a conveyor belt transporting the bill. The bill is placed on the belt with random angle and with different sides of banknote facing up. Due to the variance in the speed of the conveyor belt, the size of a bill shown in the image might be shortened or elongated. Moreover, the location of serial number with respect to the bill is unfixed. To recognize serial number with such complex variations, we proposed a system composed of two subsystems, i.e., data preprocessing and OCR, as show in Figure 2.

The first subsystem, data preprocessing, first finds the deformed bill contour and detects the skew angle of bill. It then specifies the serial number location in the bill, the number's ROI, by applying thresholding methods. Despite all abovementioned unstable conditions of the input data, the data preprocessing subsystem is able to detect the serial number location correctly.

The second subsystem, OCR, takes a binary image, which is the serial number ROI obtained from the previous subsystem. Character segmentation and character recognition are performed in this subsystem following the rules developed in section 5. In this paper, the second subsystem will be introduced in details.

4. Data preprocessing

The procedures in data preprocessing will be presented in this section. The scanned image will be taken as an input and the output will be the serial number's ROIs.

Banknote detection and location

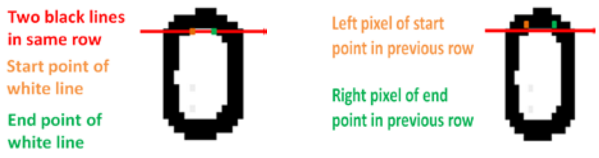
The location of banknote in the scanned image, as shown in Figure 3, will be found using the brightness difference at its boundary. Since the banknote is not precisely aligned, our system will detect its skew angle and calibrate the banknote.

Scanning conditions classification

Taking advantage of features on a bill, such as the figures and different patterns on the background, our system is able to distinguish the face from the back of bill, i.e., the flipped bill can be discriminated from the non-flipped one. Different scanning conditions are shown in Figure 4.

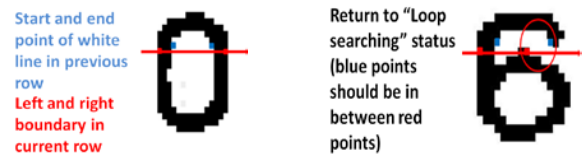
(a) (b) (c)

Figure 6. *Character segmentation*



(a) (b)

Figure 7. *"Loop entered" status (a) Record the start and end point of white line. (b) Check whether white line exists in the previous row.*



(a) (b)

Figure 8. *(a) Normal loop (b) Loop ends and the status returns to "Loop searching"*

Figure 9. *Loop ends and the status returns to "Loop searching"*

Finding ROIs of Serial number

The location of each serial number in the bill is not fixed. Due to the variance of exposure time in the scanning machine, the bill in scanned image might be deformed. As a result, our system will select a referenced point, i.e., the bill's upper left corner, and a predefined area, which is adjusted according to the aspect ratio of bill in image, as initial serial number ROI. The final ROIs, as shown in Figure 5, will be obtained by further shrinking the initial ROIs based on the distribution of dark pixels in the predefined area.

5. Optical character recognition

Optical character recognition takes a binary image, which is the serial number ROI obtained from the data preprocessing subsystem. The proposed method in section 5.1 for character segmentation finds the boundary of each character regardless of the noise and different sizes of a character. Feature of each character will then be extracted with algorithms in sections 5.2 and 5.3. Finally, the segmented character will be classified according to the rules introduced in section 5.4.

5.1 Character segmentation

In order to segment all the letters and digits in the serial number, the system has to determine the boundary of each character with horizontal scanning and vertical scanning algorithm.

Left and right boundary

Through horizontal scanning the ROI from left to right, the system marks the first black pixel as left boundary and the status becomes "intra-character". The status will then become "inter-character" if there exists no black pixels in the entire column and this column will be marked as the right boundary of the character, as shown in Figure 6 (a)

Upper and lower boundary

When the status remains "intra-character", the system will calculate the highest and lowest black pixels in each column and update the upper and lower boundary of the character, as shown in Figure 6 (b). After the boundary of a character is confirmed, the character will be segmented, as shown in Figure 6 (c). However, when the character has only 1 pixel in height or width, such character will be ignored as a noise

5.2 Loop detection

The system will scan through the ROI from left to right and from top to down pixel by pixel. This step allows the system to determine the location of loop. Two statuses, "Loop searching" and "Loop entered", are used to determine whether loops exist.

Loop searching

Once two black lines are found during horizontal scanning, the start and end point of white line between two black lines will be recorded, as shown in Figure 7 (a). Furthermore, the system checks whether the left pixel of start point and the right pixel of end point in the previous row are black. If both conditions are satisfied, the system will enter status "Loop entered", as shown in Figure 7 (b).

Loop entered

After entering the loop, the system will continuously check whether the left and right boundary contains the white line from the previous row. If the above condition fails, the status becomes "Loop searching", as shown in Figure 8. Furthermore, the system will check whether the pixels, ranging from the previous pixel of start point and next pixel of end point, are black. If the above condition is satisfied, the status becomes "Loop searching", as shown in Figure 9. Note that the start and end point is obtained from the white line in previous row.

5.3 Opening detection

The algorithm to find openings will be presented in this section. The openings have four directions and these openings are features that will be utilized to classify characters.

Leftward and rightward opening

Through vertical scanning, every pixel will be classified into 6 categories as listed in Table 1, which help to judge leftward and rightward openings. As for white pixels whose upper and lower pixels are black, another rule is applied as listed in Table 2. Category of such pixel will be determined by category of the pixel on its left. The leftward or rightward opening of a character, as shown in Figure 10 (a-c), can be determined from those 6 categories. Since the noises (or openings with only 1 pixel) will occur at the boundary after binary thresholding, which result in the openings as shown in Figure 10 (d), categories C1 and D1 are established for filtering out noises and only categories C2 and D2 will be considered as real opening.

Upward and downward opening

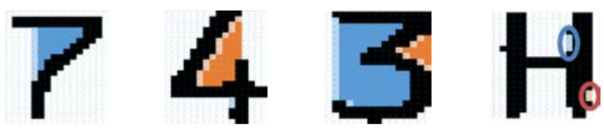
During the vertical scanning, any white area between two black lines will be colored with black. The system will detect

Table 1. Rules for leftward and rightward opening I

Category	Definition
A1	White pixel belongs to background.
B1	Black pixel belongs to character stroke.
C1 and C2	White pixel, whose upper and lower pixels are black, belongs to leftward opening.
D1 and D2	White pixel, whose upper and lower pixels are black, belongs to rightward opening.

Table 2. Rules for leftward and rightward opening II

Category of left pixel	Category of white pixel
A1	C1
C1	C2
B1	D1
D1	D2



(a) (b) (c) (d)

Figure 10. *(a) A leftward opening (b) A rightward opening (c) A leftward opening and a rightward opening (Category C1, C2, D1 and D2 are marked with light blue, blue, light orange and orange respectively.) (d) Noises generated after binary thresholding result in openings.*

Table 3. Coarse character classification. Loop and opening (with directions) are symbolized as circle and arrow respectively. The crosshair represents multiple openings.

Group	Corresponding disciplines	Character
Group 1		D, O, P, Q, 0, 4
Group 2		B, 8
Group 3		J(new version), U, V, Y
Group 4		C, E, F, G, 4(new version)
Group 5		J, 3, 7
Group 6		S, Z, 2, 3(new version), 5
Group 7		H, M, N, W
Group 8		I, L, T
Group 9		A, R, 6, 9
Group 10		K, X

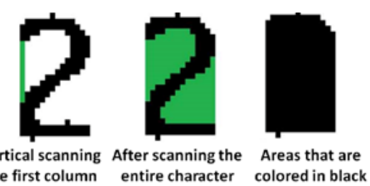
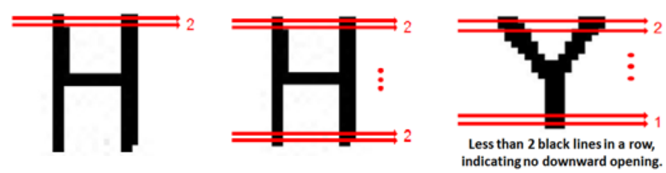


Figure 11. *Colored areas during vertical scanning procedure*

whether any upward or downward opening exists in the colored area, as shown in Figure 11. The detection procedure will be described next. Considering the top three rows of the character using horizontal scanning, if the number of black lines remains constant in two or more continuous rows, the character is said to have an upward opening, as shown in Figure 12 (a). Similarly, the system can determine whether downward opening exists, as shown in Figure 12 (b) and Figure 12 (c).



(a) (b) (c)

Figure 12. *(a) An upward opening (b) A downward opening (c) No downward opening*

5.4 Character classification

After vertical and horizontal scanning, loop and opening features can be used to classify the characters. The system takes advantage of the opening direction and the number of loops to begin with the coarse classification. Since each character may have different fonts in the latest and the previous bill versions, the same character may end up in different categories, as shown in Table 3. Rules for fine classification of each group will be presented in subsection 5.4.1 to 5.4.10

5.4.1 Rules for group 1 fine classification

- Character P: The lowest pixel in closed loop is higher than middle of the character, as shown in Figure 13 (a).
- Character 4: A white triangle exists at upper left of the character, as shown in Figure 13 (b).
- Character Q: A protruding black stroke appears in closed loop, as shown in Figure 13 (c).
- Character D: No unfilled corner exists on upper left and lower left of the character, as shown in Figure 13 (d).
- Letter O and digit 0 can be classified using their appearing position in bill serial number.

5.4.2 Rules for group 2 fine classification

- Character B: No unfilled corner exists on upper left and lower left of the character, as shown in Figure 14.

5.4.3 Rules for group 3 fine classification

- Character J: The highest pixel in upward opening is lower than the middle of character, as shown in Figure 15 (a).
- Character U: The lowest pixel in upward opening is lower than a quarter of character, as shown in Figure 15 (b).
- Letter V is not printed in the bill serial number, so no testing data is available for classification.

5.4.4 Rules for group 4 fine classification

- Characters E and G: The opening is cut into half, as shown in Figure 16 (a).
- Character E: The height of rightmost opening is larger than half of largest height in the opening, as shown in Figure 16 (b).

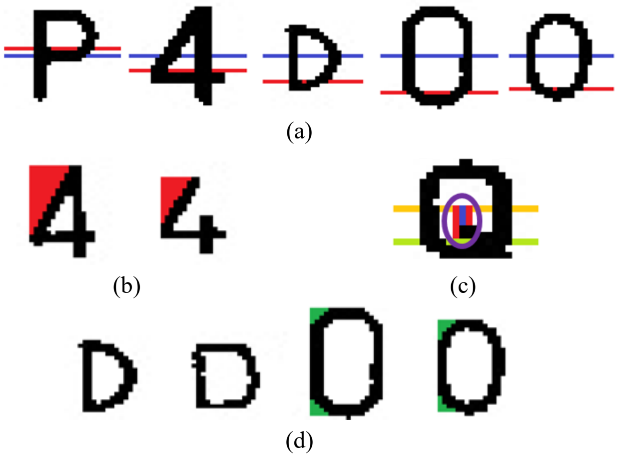


Figure 13. *Group 1 fine classification*

Figure 14. *Difference between B and 8*

Figure 15. *Group 3 fine classification*

- Character F: A large white square exists at lower right corner of the character, as shown in Figure 16 (c).
- Character 4: A large white triangle exists at upper left corner of the character, as shown in Figure 16 (d).

5.4.5 Rules for group 5 fine classification

- Character J: The end point of leftward opening is at the left of the middle of character, as shown in Figure 17 (a).
- Character 3: The opening is cut into half, as shown in Figure 17 (b).

5.4.6 Rules for group 6 fine classification

- Character 3: The start point of rightward opening is on the right of the middle of character, as shown in Figure 18 (a).
- Characters Z and 2: The start point of rightward opening is lower than the middle of character, as shown in Figure 18 (b).
- Character Z: The difference of highest point of leftward opening and highest point of rightward opening must be less than a quarter of character height. In addition, 4 corners of the character are all filled, as shown in Figure 18 (c).
- Character S: The start point of leftward opening must be the highest point in leftward opening and 4 corners of the character are unfilled, as shown in Figure 18 (d).

5.4.7 Rules for group 7 fine classification

- Character M: Two downward opening.

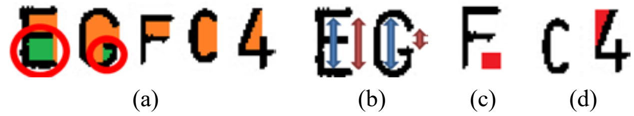


Figure 16. *Group 4 fine classification*

Figure 17. *Group 5 fine classification*

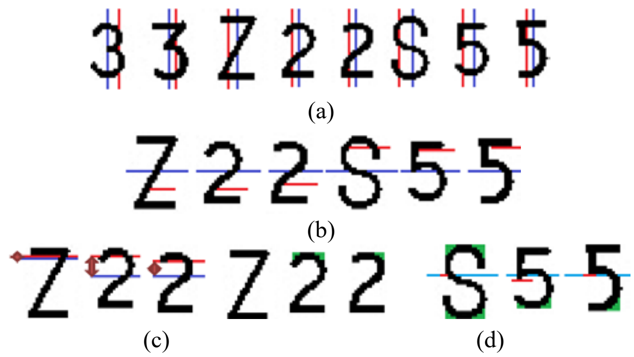


Figure 18. *Group 6 fine classification*

- Character H: No more than 2 black lines exist during horizontal scanning, as shown in Figure 19 (a).
- Character W: The difference of two white line segments at 0.25×height and 0.75×height, respectively, is more than a quarter of the character width, as shown in Figure 19 (b).

5.4.8 Rules for group 8 fine classification

- Characters L, T and 1: The width of character is less than a quarter of its height, as shown in Figure 20 (a).
- Character L: The longest stroke in the character is at the left of a quarter of character width (measured from left), as shown in Figure 20 (b).
- Character T: The longest stroke in the character is at the left of a quarter of character width (measured from the right), as shown in Figure 20 (c).
- Letter I and digit 1 can be classified using their appearing position in bill serial number.

5.4.9 Rules for group 9 fine classification

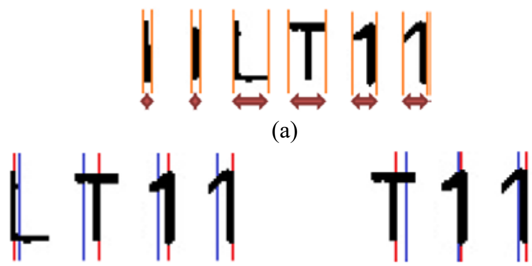
- Character A: A loop and a downward opening.
- Character R: A loop, a downward opening and a rightward opening.
- Character 6: A loop and a rightward opening.
- Character 9: A loop and a leftward opening.

5.4.10 Rules for group 10 fine classification

- Character K: An upward opening, a downward opening and rightward opening.
- Character X: An upward opening, a downward opening, rightward opening and a leftward opening.

(a) (b)

Figure 19. *Group 7 fine classification*



(a) (b) (c)

Figure 20. *Group 8 fine classification*

6. Experiment result and discussion

We have tested 2245 banknotes (RMB) and 22313 characters in total. The accuracy of horizontal serial number recognition and vertical serial number recognition are 96.34% and 98.50% respectively. In terms of character recognition accuracy, our proposed system achieves 99.35% for horizontal serial numbers and 99.84% for vertical serial numbers. Moreover, the processing time for each banknote is less than 30ms on an embedded processor with less than 8 MB memory.

7. Conclusion

In this paper, we propose a novel, ruled-based optical character recognition (OCR) system focusing on the recognition of serial number on Renminbi banknote. The ruled-based system is considered for the implementation on embedded processor, which has less than 8 MB memory available. Under such constraint, our system achieves approximate 99.6% for recognizing 22313 characters in less than 30ms per bill. The proposed scheme can be implemented easily for other embedded processors. The applicability to different fonts can be done with minor rule modifications, which are currently under investigation.

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References

[1] M. Laine, and O. S. Nevalainen, "A Standalone OCR System for Mobile Cameraphones," in *Proc. IEEE 17th Intl. Symp. on Personal, Indoor and Mobile Radio Communications*, Helsinki, 2006.

[2] Á. Gonzalez, L. M. Bergasa, J. J. Yebes, and S. Bronte, "A Character Recognition Method in Natural Scene Images," in *Proc. 21st Intl. Conf. on Pattern Recognition*, pp. 621-624, Tsukuba, 2012.

[3] M. Kumar, M. K. Jindal and R. K. Sharma, "k-Nearest Neighbor Based Offline Handwritten Gurmukhi Character Recognition," in *Proc. Intl. Conf. on Image Information Processing*, Shimla, 2011.

[4] W. Ohyama, A. Yamamoto, T. Wakabayashi, and F. Kimura, "Improving Accuracy of Printed Character Recognition using Hexagonal Zoning of Directional Histogram Feature," in *Proc. 22nd Intl. Conf. on Pattern Recognition*, pp. 2697-2702, Stockholm, 2014.

[5] A. Negi, C. Bhagvati and B. Krishna, "An OCR System for Telugu," in *Proc. 6th Intl. Conf. on Document Analysis and Recognition*, pp. 1110-1114, Seattle, 2001.

[6] S. S. Bukhari, M. I. A. A. Azawi, F. Shafait, and T. M. Breuel, "Document Image Segmentation using Discriminative Learning over Connected Components," in *Proc. 9th IAPR Intl. Workshop on Document Analysis Systems*, pp. 183-190, Boston, 2010.

[7] Z. Li, M. Schulte-Austum and M. Neschen, "Fast Logo Detection and Recognition in Document Images," in *Proc. 21st Intl. Conf. on Pattern Recognition*, pp. 2716-2719, Istanbul, 2010.

[8] J. U. Mahmud, M. F. Raihan and C. M. Rahman, "A Complete OCR System for Continuous Bengali Characters," in *Proc. TENCON 2003. Conf. on Convergent Technologies for the Asia-Pacific Region*, pp. 1372-1376, Bangalore, 2003.

[9] M. Muralikrishna, and D. Reddy, "An OCR-character Segmentation using Routing based Fast Replacement Paths in Reach Algorithm," in *Proc. Intl. Conf. on Image Information Processing*, Shimla, 2011.

[10] A. J. Newell and L. D. Griffin, "Multiscale Histogram of Oriented Gradient Descriptors for Robust Character Recognition," in *Proc. Intl. Conf. on Document Analysis and Recognition*, pp. 1085-1089, Beijing, 2011.

[11] R. Minetto, N. Thome, M. Cord, N. J. Leite, J. Stolfi "T-HOG: an effective gradient-based descriptor for single line text regions," in *Pattern Recognition*, Vol. 46, No. 3, pp. 1078–1090, 2013.

[12] S. Tian, S. Lu, B. Su and C. L. Tan, "Scene Text Recognition Using Co-occurrence of Histogram of Oriented Gradients," in *Proc. Intl. Conf. on Document Analysis and Recognition*, pp. 912-916, Washington, 2013.

[13] D. Nasien, H. Haron and S. S. Yuhaniz, "Support Vector Machine (SVM) for English Handwritten Character Recognition," in *Proc. 2nd Intl. Conf. on Computer Engineering and Applications*, pp. 249-252, Bali Island, 2010.

[14] G. G. Rajput, R. Horakeri, S. Chandrakant, "Printed and Handwritten Mixed Kannada Numerals Recognition using SVM," in *International Journal on Computer Science and Engineering*, Vol. 02, No. 05, pp. 1622-1626, 2010.

[15] J. J. Lee, P. H. Lee, S. W. Lee, A. Yuille and C. Koch, "AdaBoost for Text Detection in Natural Scene," in *Proc. Intl. Conf. on Document Analysis and Recognition*, pp. 429-434, Beijing, 2011.

[16] D. C. Ciresan, U. Meier, L. M. Gambardella, and J. Schmidhuber, "Convolutional Neural Network Committees for Handwritten Character Classification," in *Proc. Intl. Conf. on Document Analysis and Recognition*, pp. 1135-1139, Beijing, 2011.

[17] I. J. Goodfellow, Y. Bulatov, J. Ibarz, S. Arnoud, and V. Shet, "Multi-digit number recognition from street view imagery using deep convolutional neural networks," in *Proc. Intl. Conf. on Learning Representations*, Banff, 2014.

[18] J. Park and V. Govindaraju, "Active Character Recognition using "A*-Like" Algorithm," in *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 82-87, Hilton Head Island, 2000.