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A Novel Logo Detection and Recognition Framework for Separated Part Logos in Document Images

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Abstract: The procedure of detection and recognition for separated part logos in document images is a major problem in logo detection and recognition algorithms that previously have presented. In this paper, a novel logo detection and recognition framework based on spatial and structural features especially for separated part logos application is proposed. To overcome this problem, we consider some specifications of these logos such as centroid coordinates and intersection of each logo's separated part bounding box in detection process. To improve detection performance, a morphological dilation operation is used to merge separated parts of logos. In our framework, a new spatial feature for logo recognition is presented. This feature is defined based on histogram of object occurrence in a new tessellation of logo image. KNN is used to recognize the detected logos. Our proposed framework is evaluated on a public document image database for detection process and standard logo dataset of Maryland University for recognition process. The provided results show its performance in logo detection and recognition.

Key words: Logo detection, logo recognition, horizontal dilation, spatial density, feature extraction, boundary extraction, decision tree classifier, logo image normalization, black pixel histogram, KNN classification.

INTRODUCTION

Nowadays need for automatic document classification due to saving time is necessary. The document image analysis and understanding have received a great deal of interests in the last few years for many diverse applications such as, digital library, Internet publishing and searching, on-line shopping and official automation systems. The detection of logo can be considered as a reliable method for the document image analysis and retrieval. Logos are also applicable for identifying of document source. Logos are 2D shapes that have various styles and usually they are combination of graphical and text parts and etc (T. Pham, 2003).

Former researches related to logos in the document images divided into logo detection problems (T. Pham, 2003; Seiden *et al*., 1997; G. Zhu and D. Doermann, 2007; Wang and Chen, 2009; H. Wang, 2010) and logo recognition problems (Doermann, 1993; Doermann, 1996; Y.S. Kim, 1998; P. Suda, 1997; G. Zhu, 2009; M. Goria *et al*., 2003; F. Cesarini, *et al*., 1997; J. Chen, *et al*., 2003; Nagy and S. Seth, 1984). In (T. Pham, 2003) a simple logo detection method has been presented based on the assumption that the spatial density of foreground pixels in a logo region is greater than that in non-logo regions. A document image is first binarized into foreground and background pixels. Then, the spatial density within each fixed size window is computed and the region with the highest density is hypothesized as a logo region. In (S. Seiden, *et al*., 1997), a logo detection system has been presented based on segmentation the document image into smaller images using a top-down X-Y cut algorithm (S. Seiden, *et al*., 1997). In this paper, sixteen features of the connected components in each segment are extracted and used by a rule-based classification scheme. In (G. Zhu and D. Doermann, 2007), an approach to logo detection and extraction in the document images using a multi-scale boosting strategy has presented. An initial two-class Fisher classifier at a coarse image scale on each connected component is used. Each detected logo candidate region is then classified at finer image scales by a cascade of simple classifiers (G. Zhu and D. Doermann, 2007). In [8], a method for such a system based on the image content, using a shape feature has presented. Zernike moments of an image are used as a feature set. In this method, to recognize the detected logo, a similarly measure based on shape feature (Zernike moments) has defined. In (P. Y. Yin, C. C. Yeh, 2002), an automatic content-based logo retrieval method has proposed. The proposed method in (P.Y. Yin, C.C. Yeh, 2002) automatically selects appropriate features (such as area, deviation, symmetry, centralization, complexity and 2-level contour representation strings) based on feature selection principles to discriminate logo. In this method, the user can submit a query through logo examples to get a list of database trademarks ordered by similarity ranks. In (M. H. Hung, 2006), a shape-based similarity retrieval system has developed based on database classification, which exploits the contour and interior region of a shape efficiently. In this paper, angular radial transform (ART) region feature is employed to compare the query with the candidate sets according to the priority order. In (I.S. Hsieh, K.C. Fan, 2001), a color image retrieval system based on multiple

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classifiers has presented. In this approach, a region-growing technique for segmentation of the input image into logo candidate regions and three complementary region-based classifiers (color, shape and relational classifiers) have applied o logo recognition. In each classifier, a virtue probability representing the probability that an image is similar to the query image is defined. A set of virtue probabilities is calculated to define similarity measure in each classifier.

The detection of separated-part-logo usually is a challenge in logo detection problem. So in this paper, we propose an algorithm that improves the performance of logo detection with this challenge. In this paper, centroid coordinates in vertical direction and intersection of each separated part logo bounding box are two major specifications that we use to improve the logo detection procedure. In recognition process, we propose a novel feature based on histogram of object occurrence in a new tessellation of logo image.

The remainder of this paper is organized as following: In next section, we introduce the proposed logo detection algorithm. The proposed logo recognition algorithm is described in section 3 in detail. Experimental results are obtained in section 4. Finally, the summarizing remarks are given in section 5.

2. Logo Detection:

Fig. 1 shows block diagram of logo detection algorithm. This algorithm consists of a noise reduction procedure, image binarization, dilation morphological operation, decision tree classifier and ultimately logo detection and modification procedures. The details of these procedures are described in the following sections.

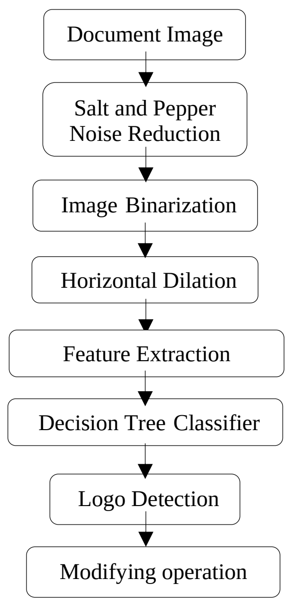


Fig. 1: Block diagram of the proposed logo detection algorithm.

2.1. Salt And Pepper Noise Reduction:

In the first section, the salt and pepper noise in document images is reduced using median filter. Note, that filter size is restricted due to diverse quality of the document images. It is possible, which any part of logos in the degraded document images is removed.

2.2. Image Binarization:

After noise reduction procedure, a binarized image $g(x, y)$ is defined as:

$$g(x, y) = \begin{cases} 1, & if\ f(x, y) > T \\ 0, & if\ f(x, y) \leq T \end{cases} \tag{1}$$

where $f(x, y)$ and T are the gray level of point (x, y) and threshold value of binarization, respectively and $g(x, y)$ is binary image. The pixel values of $g(x, y)$ that label to zero and 1 corresponding to background and object, respectively.

2.3. Horizontal Dilation Operation:

Dilation is one of the basic operations in mathematical morphology. The dilation operation usually uses a structuring element for probing and expanding the shapes involved in the input image. With A and B as sets in Z^2, the dilation of A by B, denoted $A \oplus B$, is defined as:

$$A \oplus B = \{z | (\hat{B})_z \cap A \neq \varnothing\} \tag{2}$$

This equation is based on obtaining the reflection of B about its origin and shifting the reflection by z.

2.4. Feature Extraction Of Regions:

After applying dilation operator on the binary image of the document image, binary object regions are formed. Every region has a bounding box that surrounds it. We use some properties of these bounding boxes as features. These features are width and height of the logo regions, and aspect ratio. Aspect ratio is defined as ratio of width to height. Another feature that has key role in classifying of logo and non-logo regions is spatial density (T. Pham, 2003) of each region in own bounding box. Note that we have to normalize the size of each bounding box to specific size, before computing of spatial density.

2.5. Decision Tree Classifier:

A simple decision tree for classifying of logo and non-logo regions is shown in Fig. 2. This classifier has been designed so that false accepts from logo candidate is decreased. In this decision tree, decision makes based on three features (width and height, aspect ratio, spatial density features) in three steps. The sequence of this decision tree is formed based on making decision from low complexity through high complexity.

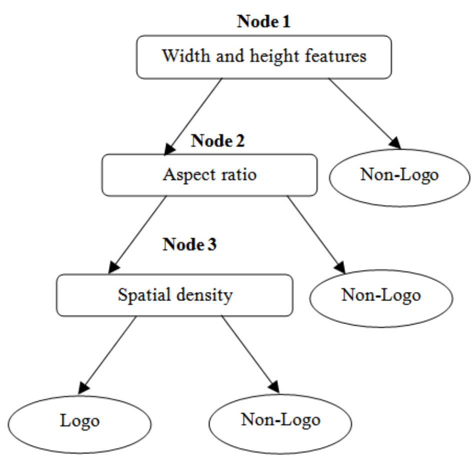


Fig. 2. Decision Tree Classifier with three nodes.

2.6. Modifying Operation:

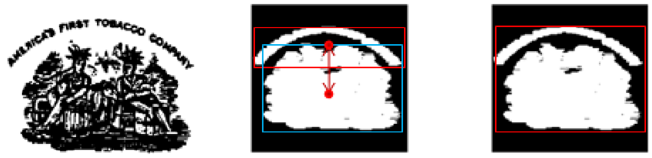
In this section, we want to modify results of our logo detection algorithm based on knowledge that most separated-part-logos usually have one or both of these following specifications:

1) The centroid coordinate of each separated-part-logo bounding box in vertical direction is equal.
2) The intersection of each separated-part-logo bounding box is unequal to null.

Note that the gap between each logo part must be less than a given threshold. We define modifying rules based on above specifications as follow:

If One Or Both Of Above Specifications Are Satisfied, Merging Operation Will Be Done:

The procedure of our algorithm as follows: After classifying of logo and non-logo in own classes using the decision tree classifier, modifying operation is used to reduce false reject from logo candidate based on the defined rules. Fig. 3 and Fig. 4 illustrate performance of these rules on logo and non-logo classification procedure.



(a) (b) (c)

Fig. 3: (a) Main logo. (b) Both of specification satisfied. (c) Merging process.

Fig. 4: Merging operation based on the first specification.

3. Logo Recognition:

Block diagram of our proposed algorithm for logo recognition is shown in Fig. 5. In this algorithm, after boundary extraction of logo region and logo normalization, bounding box of the logo region is tessellated into the same size blocks and a new spatial feature extracted. In the next step, a KNN classifier is used to recognize logo regions. In the following, we describe these sections in details.

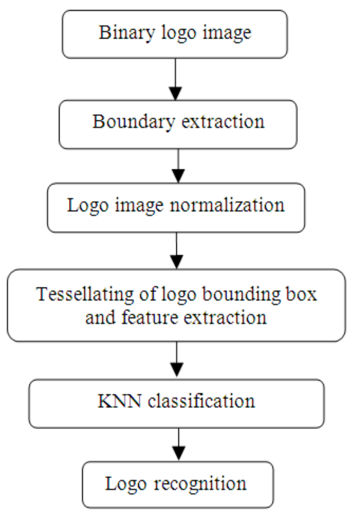


Fig. 5: Block diagram of the proposed logo recognition algorithm.

Fig. 6: Extracted boundary of a sample logo.

3.1. Boundary Extraction:

In this step, we extract the boundary of binary logo image which is necessary for logo normalization. The output of this section is the coordinates of logo boundary pixels. Note, before boundary extraction thinning process of logo region is carried out. If $p_1(x_1, y_1), p_2(x_2, y_2),..., p_n(x_n, y_n)$ are sequences of integer coordinate points of logo boundary, the following conditions must be satisfied:

$$\left|x_i - x_{i+1}\right| \le 1 \text{ and } \left|y_i - y_{i+1}\right| \le 1 \tag{3}$$

where those conditions can not equal to zeros simultaneously. Fig.6 shows the extracted boundary of a sample logo.

3.2. Logo Image Normalization:

Logo image normalization is a major part in logo recognition procedure. The purpose of normalization is to eliminate or reduce the logo recognition sensitivity to image orientation and size. The normalization process includes two sections. In the first section, we normalize the logo size. For this purpose, we compute the major axis length and normalize it based on specific size. Major axis is a line segment that connects two farthest points on the boundary based on Euclidean distance. This line segment is not always unique, but it is considered as a useful descriptor. If $(x_1, y_1),(x_2, y_2),...,(x_n, y_n)$ are coordinates of logo boundary, we denote major axis length by *lma* and define it as:

$$lma = \max\left[(p_i - p_j)^T (p_i - p_j)\right]^{0.5} \tag{4}$$

where, p_i is *i-th* pixel with coordinate (x_i, y_i), p_j is *j-th* pixel with coordinate (x_j, y_j), for $1 \le i, j \le n$ and $i \ne j$. Fig. 7 shows the major axis of a logo sample and the result of size normalization of this is shown in Fig. 8.

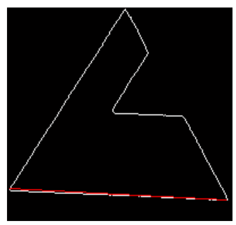


Fig. 7: Major axis of a logo sample.

Fig. 8: Normalization result of the shown logo in Fig. 7.

Fig. 9: (a) Main logo. (b), (c) and (d) its representation for three reference lines.

In the second section, we normalize the orientation of the logo image. At first, we choose several reference lines (J. Chen, 2003) of logo image and for each reference line we have a new representation. The angle of each reference line with horizontal direction must be zero. Obviously, more reference lines lead to better results but computation time will be increased. Fig. 9 shows some logo representation for each reference line that has been highlighted by red color.

3.3. Tessellating Of Logo Bounding Box And Feature Extraction:

After normalization section, we define a novel feature for logo recognition that is extracted in two steps as following:

Tessellating of each bounding box: In this step, the bounding box of each logo image is partitioned to equal block. The choice of block size is important so that if it is selected very small, the recognition process will lead to error in noisy images and if it is selected very large, the extracted feature will not be useful. After several experiments, it found that the block size must be proportioned with bounding box size and this choice will lead to best result.

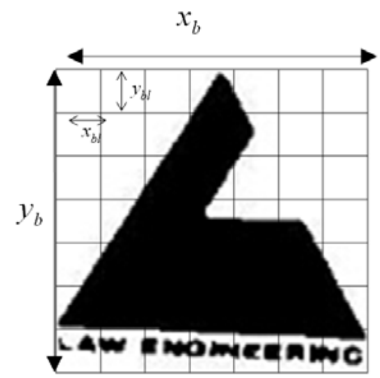


Fig. 10: Blocking of bonding box of a logo sample.

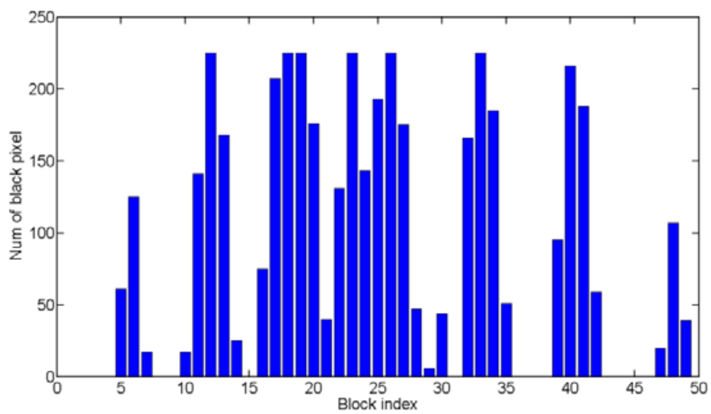


Fig. 11: histogram of the black pixels for each block.

We define the ratio between block size and bounding box size as *α* parameter. If x_{bl}, y_{bl}, x_b and y_b represent the block length, block width, bounding box length and bounding box width respectively, the relations between block size and bounding box size is shown as follows:

$$x_{bl} = \alpha \times x_b \tag{5}$$

$$y_{bl} = \alpha \times y_b \tag{6}$$

Based on our experiments, the best value for *α* parameter is 0.16. The results of recognition process for various value of *α* parameter with various salts and pepper noise density are shown in Table 4.

3) *Feature extraction:* In this step, feature vector for classifying operation are extracted. After tessellation of the bounding box of logo image, we compute the number of black pixels in each block from top through down and denote it as $f_1, f_2, f_3, ..., f_n$ where f_i the number of black pixel in *i-th* block, ($1 \le i \le n$) and *n* is the number of blocks in each bounding box of logo image. Fig. 10 shows blocking of the bounding box of a logo sample and Fig. 11 shows histogram of the black pixels in each block. In Fig. 11, horizontal and vertical axes represent block index and the number of black pixels in each block, respectively.

3.4. K- Nearest Neighbourhood Classification:

Among the various methods of supervised statistical pattern recognition, K-Nearest Neighborhood classifier achieves consistently high performance, without a priori assumptions about the distributions from which the training examples are drawn. It involves a training set of both positive and negative cases. An unknown sample is classified by calculating the distance to the nearest training prototype. Then, the label of this unknown sample is determined based on classification result. The KNN classifier extends this idea by taking the

k nearest points and assigning the label of the majority. It is common to select k small and odd values to break ties (typically 1, 3 or 5). Larger k values help to reduce the effects of noisy points within the training data set, and the choice of k is often performed through cross validation.

4. Experimental Results:

The proposed logo detection and recognition framework is evaluated on tobacoo-800 dataset [18] which is composed of 1290 document images. There are 416 document images that involve logo. We use 120 documents that include logo as the train dataset and remaining documents used as test dataset. Experimental results on logo detection and recognition are obtained in two sections separately.

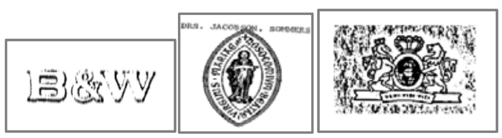
4.1. Evaluation Parameters:

We evaluate performance of our proposed framework based on the presented measure in (G. Zhu and D. Doermann, 2007). According to Zhu approach, logo detection process is successful “if and only if the detected region contains more than 75% pixels of a ground truth logo and less than 125% of the area of that ground truth logo’’. We define accuracy and precision measures for performance evaluation as:

$$Accuracy = \frac{\#\ of\ corrected\ detected\ logos}{\#\ of\ logos\ in\ ground\ truth} \quad (7)$$

$$Precision = \frac{\#\ of\ corrected\ detected\ logos}{\#\ of\ detected\ logos} \quad (8)$$

Fig. 12: Some logos that detected successfully by the proposed algorithm.



(a) (b) (c)

Fig. 13: Unsuccessful logo detection. (a) incomplete logo, (b) logo adhesion with other document parts, (c) much noise surrounding logo region.

Table 1: Decision Tree Classifier Rules In Each Node.

Node #	Feature	Range
1	$\frac{\text{bounding box width}}{\text{image width}}$	[0.04, 0.39]
	$\frac{\text{bounding box height}}{\text{image height}}$	[0.032, 0.23]
2	aspect ratio	[0.39, 4.95]
3	spatial density	[3.8, 31]

4.2. Logo Detection Results:

To tune our logo detection algorithm, we have to choose suitable value for structuring element in the horizontal dilation. We found heuristically that if width of the document image is considered as W, selection of W/100 value as structuring element size in the horizontal dilation will be obtained the best results. In the second step, we compute decision tree classifier values in each node. As previously mentioned, we use 120 documents which contain logos for training of the decision tree classifier to classify logo and non-logo due to reduce false accept ratio in the logo candidate detection step. Table 1 shows decision rules for each node in the decision tree classifier. In Fig. 12, some logos have shown that successfully detected by the proposed algorithm. Fig. (13-a) shows incomplete logo that rejected by the decision tree classifier. Fig. (13-b) shows logo adhesion with text part led to unsuccessful detection. Fig. (13-c) shows unsuccessful logo detection due to much noise around logo region.

4.2. Logo Recognition Results:

We evaluate our proposed logo recognition algorithm on logo database from university of Maryland [19]. It includes 105 logo images in the TIFF format. In Fig. 14, some logos which are used in our tests are shown ((a) origin logos, (b) Strip corrupted logos and (c) partially occluded logos). Totally, five main tests have been carried out on this database as following:

1) ***Test 1***: it contains 40 logo images without any variation in size and orientation in comparison with original logo images. The proposed approach recognized all of 40 logo images correctly and the recognition rate of 100% is obtained.

2) ***Test 2***: it contains 40 logo images that are corrupted by black strip. The recognition rate of 95% is obtained.

3) ***Test 3***: it contains 40 logo images that are partially occluded. The recognition rate of 92.5% is obtained. The results of *test 1*, *test 2* and *test 3* are given in Table 2.

4) ***Test 4***: it demonstrates the effect of salt and pepper noise on recognition process and includes two subtests as following:

a. **Subtest 1**: it contains 105 logo images that are corrupted by salt and pepper noise density from 0.01 ascendantly until the recognition operation is performed correctly. This work is done for all of 105 logo images and a threshold value of noise density for each logo image is obtained. After averaging these threshold values, the most acceptable of salt and pepper noise density is 0.34.

b. **Subtest 2**: it contains 40 logo images that are corrupted by salt and pepper noise density with values 0.02, 0.04, 0.06, 0.08 and 0.1 respectively. For each density value, we repeat each test 20 times with various values of α from 0.05 through 0.25. The results of this subtest are shown in Table 3.

5) ***Test 5*:** it contains 105 logo images and demonstrates the effect of size variations of logo images in a distinct direction. These changes include scaling in horizontal and vertical directions. For this purpose, we scale the logo images in each direction separately until the recognition operation is performed correctly. The results are shown in Table 4.

(a)

(b)

(c)

Fig. 14: The used logo images in the second and tertiary test. (a) origin logos, (b) Strip corrupted logos and (c) Partially occluded logos.

Table 2: Recognition Rate For Various Test Types .

Test logo type	**Number of test logos**	**Recognition rate**
Origin logo	40	100%
Strip corrupted logos	40	95%
Partially occluded logos	40	92.5%

Table 3: Logo Recognition Results For Various Value Of α Parameter With Various Salt And Pepper Noise Density.

Noise density	**α**	**Recognition r**	**Noise density**	**α**	**Recognition r**	**Noise density**	**α**	**Recognition r**	**Noise density**	**α**	**Recognition r**	**Noise density**	**α**	**Recognition r**
	0.05	94%		0.05	90%		0.05	88%		0.05	82%		0.05	80%
	0.06	96%		0.06	92%		0.06	90%		0.06	86%		0.06	83%
	0.07	95%		0.07	90%		0.07	88%		0.07	85%		0.07	82%
	0.08	94%		0.08	91%		0.08	87%		0.08	83%		0.08	80%
	0.09	93%		0.09	91%		0.09	88%		0.09	85%		0.09	83%
	0.1	96%		0.1	93%		0.1	90%		0.1	89%		0.1	85%
	0.11	96%		0.11	94%		0.11	93%		0.11	92%		0.11	92%
	0.12	97%		0.12	94%		0.12	93%		0.12	92%		0.12	88%
	0.13	94%		0.13	92%		0.13	89%		0.13	86%		0.13	84%
	0.14	97%		0.14	95%		0.14	96%		0.14	93%		0.14	92%
0.02	0.15	97%	0.04	0.15	94%	0.06	0.15	93%	0.08	0.15	91%	0.1	0.15	90%
	0.16	98%		0.16	97%		0.16	96%		0.16	96%		0.16	95%
	0.17	92%		0.17	88%		0.17	87%		0.17	82%		0.17	79%
	0.18	97%		0.18	94%		0.18	94%		0.18	92%		0.18	91%
	0.19	98%		0.19	97%		0.19	97%		0.19	96%		0.19	93%
	0.20	95%		0.20	90%		0.20	89%		0.20	86%		0.20	84%
	0.21	97%		0.21	96%		0.21	94%		0.21	92%		0.21	91%
	0.22	98%		0.22	97%		0.22	96%		0.22	95%		0.22	93%
	0.23	98%		0.23	97%		0.23	95%		0.23	95%		0.23	93%
	0.24	97%		0.24	96%		0.24	96%		0.24	95%		0.24	93%
	0.25	92%		0.25	85%		0.25	83%		0.25	80%		0.25	78%

Table 4: The Effect Of Size Variations Of Logo Images In A Specific Direction.

Threshold value of logo size variations for correct recognition			
Vertical direction		Horizontal direction	
89 pixels	41 pixels	103 pixels	50 pixels
75%	31%	74%	33%

Based on the obtained results, one of the powerful features of our proposed algorithm is recognition of noisy logo images. Fig . 15 and Fig. 16 show a comparison between origin logo image without any noise and a logo image that is corrupted by a salt and pepper noise with density 0.2. As you can see in Fig. 15 and Fig. 16, histograms of black pixels for two logo images are approximately similar. This fact implies effectiveness of this feature in against of noisy image.

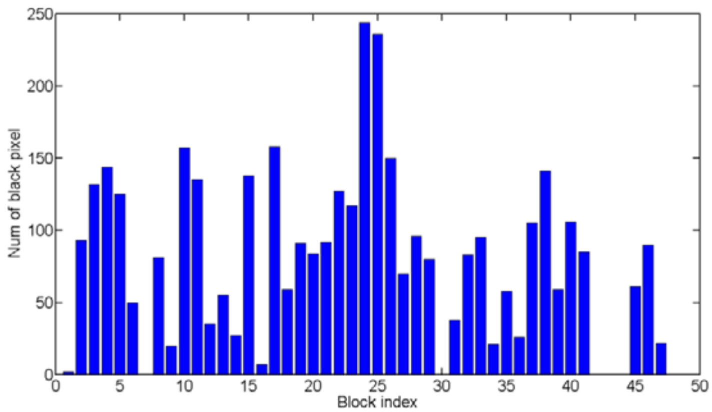


Fig. 15: Origin logo image without any noise and histogram of black pixels for each block.

5. Conclusions:

In this paper, we proposed a novel algorithm for logo detection and recognition in document images. Pre-processing step performed by median filter so that the quality of logo regions enhanced. We used horizontal dilation to merged separated parts of logo in horizontal direction as connected component. Logo and non-logo Classification was carried out using decision tree classifier with three nodes based on three width and height, aspect ratio and spatial density features of bounding box surrounding logo. The final step in our algorithm was modification operation that modifies decision tree classifier to merge regions of separated-part-logo based on the defined specifications. After logo image detection, recognition process was started by boundary extraction, normalization based on major axis and reference line of the detected logos. The histogram of black pixels was extracted from the tessellated bounding box of the detected logo image. Ultimately, KNN classifier was used to recognize the detected logos. To evaluate performance of our proposed algorithm, different tests were designed. The obtained results emphasized effectiveness of the proposed algorithm in noisy and separated part logos.

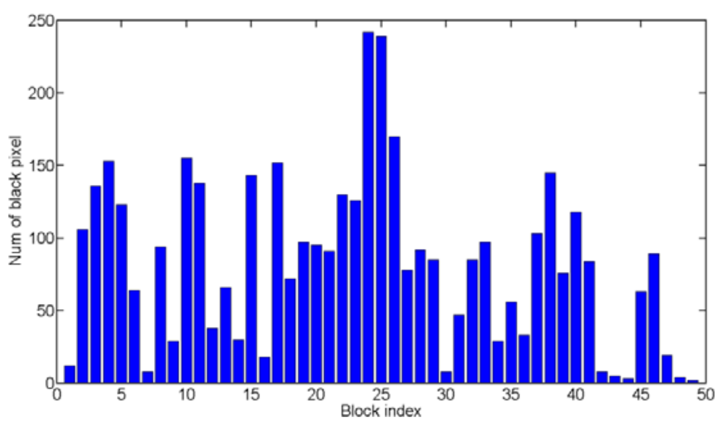


Fig. 16: Logo image that is corrupted by a salt and pepper noise with density 0.2 and histogram of black pixels for each block.

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