



Automatic logo detection from document image using HOG features

Umesh D. Dixit¹ · M. S. Shirdhonkar² · G. R. Sinha³

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Abstract

Document image analysis and processing has drawn the attention of many researchers due to its real-time applications in day-to-day life. Document database comprising of logo provides a good opportunity for an easier way of indexing, searching and retrieval of the documents. Logo detection is an essential need for the implementation of any logo-based document indexing or retrieval techniques. This paper aims to develop an efficient logo detection method for document images. The major steps employed in the developed system include preprocessing of the input document, finding the connected components and classification of these components into the logo and non-logo candidates. The preprocessing step employs a median filter and a unique procedure for the removal of clutter noise to reduce the false detection rate. Histogram of Oriented Gradient (HOG) features and an SVM classifier are used to identify the logo and non-logo candidates of the document. The presented system is evaluated using Tobacco 800 dataset and the results are compared with existing techniques. The results show an improvement of 5% in average logo detection rate with the proposed work.

Keywords Connected components · Logo detection · Document image processing · HOG · SVM · Logo detection rate

✉ Umesh D. Dixit
uddixit@rediffmail.com

M. S. Shirdhonkar
ms_shirdhonkar@rediffmail.com

G. R. Sinha
gr_sinha@miit.edu.mm

¹ Department of Electronics & Communication Engineering, BLDEA's V. P. Dr. P. G. Halakatti College of Engineering and Technology, Vijayapur 586 103 Karnataka, India

² Department of Computer Science and Engineering, BLDEA's V. P. Dr. P. G. Halakatti College of Engineering and Technology, Vijayapur 586103 Karnataka, India

³ Myanmar Institute of Information Technology (MIIT), Mandalay, Myanmar

1 Introduction

The documents available in the form of an image are referred to as document images. PDF files, newspapers, e-books are some of the examples of document images. Storage of documents in the form of images has become very popular due to easily available scanning devices and the applications that enable mobile phones to be used as document scanners. Figure 1 shows sample document images.

Many real-time applications require suitable techniques for processing, analyzing, indexing and searching the documents from a huge database [11, 22]. A large number of documents contain a logo for authentication purposes. The logo is a graphical symbol used in documents for authentication. A logo may belong to one of the three categories such as graphical logo, textual logo, or a combination of graphics and text. The graphical logo comprises entirely of graphical elements, the textual logo contains the name of the company or organization with the artwork. The third category includes a combination of first and second. Figure 2 shows examples for these three categories of logos from the publicly available Tobacco-800 database.

The presence of a logo in the document provides an opportunity for logo-based document image searching in organizations, business offices, digital libraries, etc. The successful searching of such documents mainly depends on the performance of the logo detection algorithm. Automatic logo detection from document images is also useful in the applications such as logo recognition, logo matching and logo-based document retrieval. Most of the logo detection techniques proposed in the literature depend on the density of the pixels and the features of connected components. However, these approaches could produce results with limited performance.

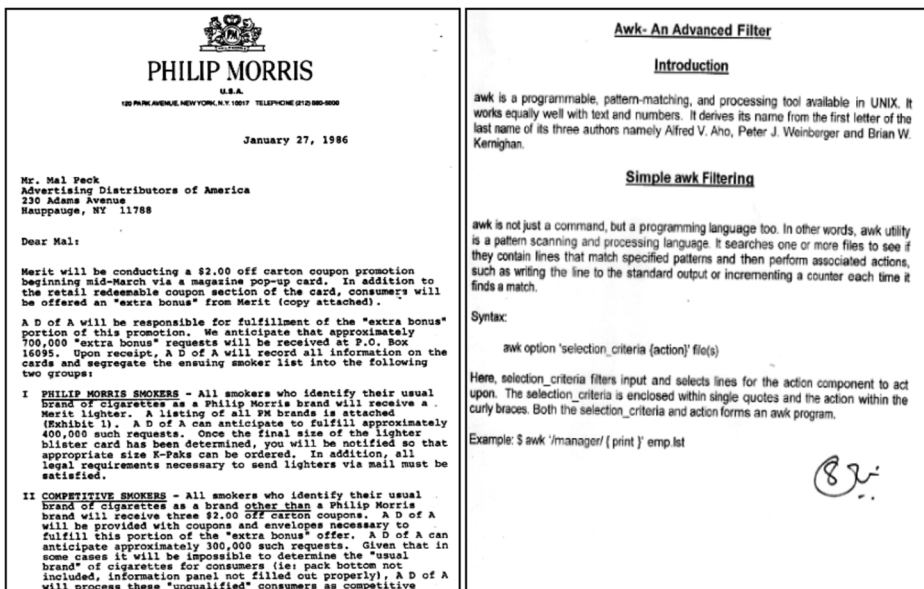


Fig. 1 Sample document images



Fig. 2 Logo categories (a) Graphic logo (b) Textual logo (c) Mixed logo

This paper aims to present an efficient logo detection method from a document image. The paper presents an automatic logo detection technique using the following steps.

- Finding the connected components.
- Analyzing the connected components.
- Extracting their features and finally classifying these components as the logo or non-logo candidates.

The main contribution of this paper includes proposing preprocessing techniques to minimize false logo detection rate and developing the techniques for automatic logo detection using HOG features and SVM classifier. The rest of this paper is organized as under: Section 2 details the existing literature, Section 3 provides an implementation of the proposed system, Section 4 provides the experimental results and Section 5 concludes the work.

2 Literature review

As part of this work, a detailed literature review is carried out to study the different methods proposed by the researchers. This section briefly highlights the state of art techniques developed for logo detection from the document image.

Seiden et al. [24] proposed a logo detection method by segmenting the document into a small set of components. Later they used a set of sixteen region-based features to differentiate the segments as logo and non-logo segments. The presented method was evaluated on a set of 130 business documents. Their method suffered from detecting textual logos. Logo detection technique using the spatial density of the pixels is proposed by Pham [23]. This method divides the document image into small windows of fixed size. For each window, the spatial density of the pixels is computed and the window with higher spatial density is assumed to have a logo part of the document. The method is tested using the UMD logo database having 105 logos with different conditions. The main advantage of this method was computationally cheap and practically simpler to implement.

Novel logo detection employing a multi-scale boosting strategy was presented by Zhu and Doermann [29]. At the initial level, the connected components with the fisher classifier are used to detect a set of probable logo candidates. Then a cascaded set of classifiers are used for logo detection at the final level. They tested the method on realistic complex document images of the Tobacco 800 dataset. Logo detection and recognition system employing spatial and structural features were developed by Hassanzadeh and Pourghassem [13]. The goal of their work was to detect and combine separated parts of logos present in the document. Histogram of object occurrence-based feature is proposed for detecting the logo parts and a morphological dilation is employed for merging. Logo recognition is implemented by using the K-NN classifier. The presented technique was investigated on a database of Maryland University.

Nejad and Faez [20] proposed a logo extraction method with two steps. In the first step, the location of the logo is identified using horizontal and vertical analysis of the pyramidal tree structure. Later for logo extraction, they applied the boundary extension of the feature rectangle. The K-NN classifier is used for logo recognition. A DWT [2, 3] based logo detection technique was presented by Shirdhonkar and Kokare [25]. This method divides the document into smaller regions, whose size is almost the same as that of logos. For each smaller region, they compute the energy of wavelet coefficients and classify the region having the highest energy as logo part of the document image.

Wang and Chen [27] proposed a new method of logo detection using boundary extension of feature rectangle. "A feature rectangle is a minimum virtual rectangle which fully embraces at least one foreground pixel (black) with four edges consisting of all background pixels (white) and has minimum inner area". With the assumption that the logos will have a white background, a seed pixel of 3×3 neighbor is defined. All the neighboring pixels from the seed are included as part of the logo, till white pixels are encountered. This approach will create a set of probable logo candidates, which are then fine-tuned for accurate logo detection using a decision tree. Dixit and Shirdhonkar [8, 10] presented the usage of HOG features for retrieval of documents based on the scripts used in multi-lingual documents. The results of logo detection proposed in [31] were improved using a cascade of classifiers. A two-dimensional shape context features are proposed for document retrieval. These features are matched using neighborhood graph matching for ranking the documents. Jain and Doermann [15] developed a logo retrieval approach using Speed Up Robust Features (SURF) [1]. An indexing scheme combining local features and geometrical constraints was presented for a huge-sized database of documents.

Dixit and Shirdhonkar proposed automatic logo detection and logo-based document image retrieval in [5, 6]. They used Singular Value Decomposition (SVD) tool and its features for logo detection and retrieval. The use of SVD features is also presented in [7] for the retrieval of face-based document image retrieval. Le et al. [18] presented a new technique of document retrieval based on logo spotting and recognition. Initially, they match the key points of the query logo and the documents stored in the database in the Scale Invariant Feature Transform (SIFT) feature space. The logos are segmented using a spatial density-based approach and homography. The number of matched key points is used as a metric for ranking and retrieval of documents. Meethongjan et al. [19] propose the use of HOG features for the detection of vehicle logos by employing a sparsity score. A weakly-supervised saliency map with convolution neural network-based logo detection is presented by Kumar et al. [17]. Dixit and Shirdhonkar [9] presented fingerprint-based document image retrieval using multi-resolution

LBP features. They applied LBP on the multi-resolution image components obtained by using DWT. Zhao and Wang presented a method for vehicle-logo detection using modified HU invariant moments and an SVM classifier [28]. Guan et al. [12] developed an algorithm for video logo retrieval. They used spatial local image-based features with a distance measure for matching query images with stored video image features. Table 1 summarizes the review of important works carried out on various logo detection techniques.

Research gap and motivation From the literature, it is revealed that most of the techniques presented for logo detection depend on the density or energy of the pixel contributed by the logo part of the documents. These techniques consider part of the document with the highest energy or density as a logo and they fail to detect if there exist multiple logos in a single document. The performance of the logo detection can be improved by adding a classifier after the detection of a set of probable logo candidates. The presence of a classifier also provides a solution for the detection of multiple logos from the document. It was found in the literature that the combination of HOG features and SVM classifier provided better classification results. Hence we are motivated by the previous works and proposed a technique that includes an SVM [21], [26] classifier with HOG features [4] for improving the detection of probable logo candidates








3 Proposed method

The idea behind the proposed technique is to find patches of document images and classify these patches as logo-patch or non-logo patches using a classifier. Figure 3

Table 1 Summary of logo detection techniques

Author [Citation]	Methodology	Limitations/Remarks
Seidan et al. [24]	Used region-based features on segmented components of the document for logo detection.	Suffered from textual logo detection
Pham [23]	Spatial density of the pixels present in partitioned windows of the document is used for logo detection.	Absence of Classifier and provision to improve the logo detection rate
Zhu and Doermann [29]	Connected components with fisher classifier was employed.	Possibility to improve logo detection rate with new set of features and classifiers.
Hassanzadeh and Pourghassem [13].	Worked to combine separated parts of logo. Used spatial and texture features with K-NN classifier for logo recognition.	Logo recognition was carried out on Maryland University database. Not evaluated for complex document images.
Shirdhonkar and Kokare [25]	Used DWT based features to compute density of pixels of partitioned regions.	Absence of Classifier and provision to improve the logo detection rate
Dixit and Shirdhonkar [5]	The energy of the connected components was computed using SVD. Connected component with highest energy is considered as logo candidate.	Absence of Classifier provision to improve the logo detection rate
Meethongjan et al. [19]	Used HOG features and sparsity score for vehicle logo detection	Not tested for complex document images.
Zhao and Wang [28]	Implemented vehicle logo detection using modified HU invariant moments and an SVM classifier	Not tested for complex document images.

Table 2 Comparison of results

Sl. No	Logo Type	Number of Document Images	DWT based Method [10]		SVD based Method [17][19]		Multi-resolution LBP features [23]		Proposed Method	
			Correctly Detected Logos	Detection Rate	Correctly Detected Logos	Detection Rate	Correctly Detected Logos	Detection Rate	Correctly Detected Logos	Detection Rate
1		54	49	90.7	51	94.4	52	96.3	53	98.1
2		65	46	70.7	63	96.9	63	96.9	63	96.9
3	<i>Levillard</i>	54	42	77.7	53	98.1	53	98.1	53	98.1
4		10	3	30	8	80	8	80	9	90
5	B&W	42	16	38.1	27	64.3	27	64.3	35	83.3
6		23	20	86.9	21	91.3	22	95.7	22	95.7
7		31	4	12.9	30	96.7	30	96.7	30	96.7
8		6	6	100	6	100	6	100	6	100
9		10	4	40	9	90	9	90	100	100

shows an overview of the proposed logo detection system. The important phases include preprocessing, generating patches of document images, Extracting HOG features, Training SVM and classifying whether the patches of input image contain a logo.

3.1 Preprocessing

The preprocessing step aims to prepare the document image for processing to have efficient results. Usually, the scanned documents suffer from salt and pepper noise. The pepper and salt noise generally correspond to pixels with the highest and lowest intensities. The best solution to remove this type of noise is replacing pixels representing noise in a window with their median value. Therefore, in this step, we pass the document image through a median filter [16]

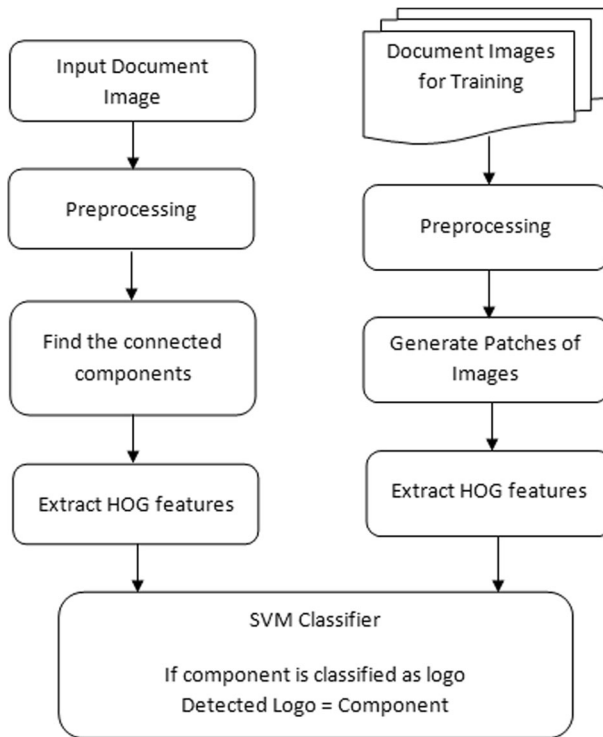


Fig. 3 Architecture of proposed logo detection

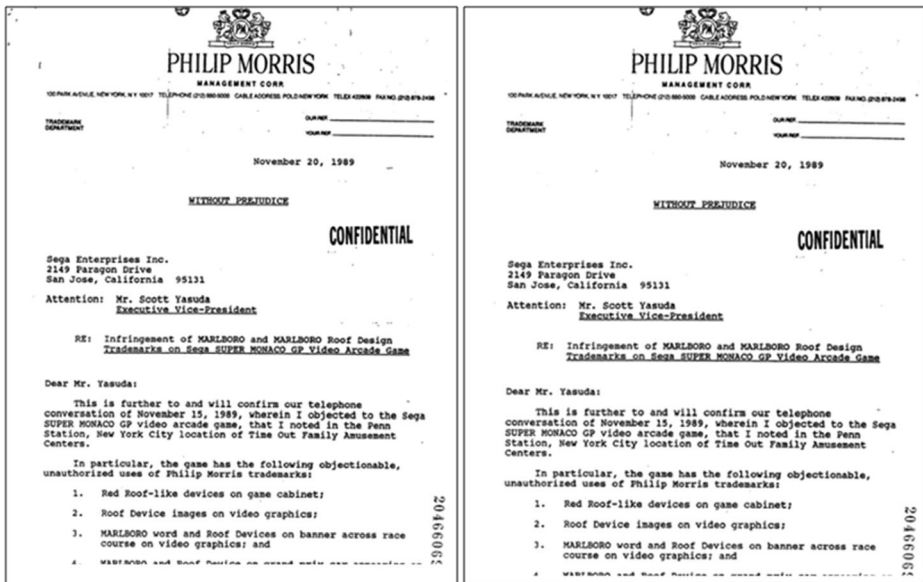


Fig. 4 (a) Before median filtering (b) After median filtering

of size 3×3 mask. Application of median filter on document 'D' can be represented by Eq. (1).

$$D = \text{Median}\{D(X, Y)\} \quad (1)$$

A median filter computes the median of the 3×3 pixels and replaces the center pixel with the computed median value. This process helps in removing isolated black-colored and white-colored pixels from the document image. Figure 4 shows a document image before and after applying the median filter. The input image comprises a scattered set of black-colored pixels at different locations appearing as pepper noise. It can be observed that the filtered document image is free from a scattered set of black-colored pixels particularly at the upper left corner of the example image.

The filtered image is then processed to remove the clutter noise or edge noise [14]. This step helps in reducing the detection of non-logo candidates and thereby it reduces the chance of false logo detection. The clutter noise appears in the form of black strips during the scanning process of the documents. For removal of clutter noise, we search for a continuous set of black pixels in the horizontal or vertical direction with a size greater than twice the average width of the logo and replace them with white (background) color. The purpose of using $2 \times (\text{average logo width})$ is to prevent the loss of information present in the logo while removing the noise. Algorithm 1 shows the steps used in preprocessing.

Algorithm 1: Preprocessing

1. Begin
Input: Document (D)
Output: Preprocessed document (DP)
2. Convert RGB image to Grayscale.
3. Apply the median filter using a mask of size 3×3 .
4. Count foreground pixels horizontally
If Count $> 2 \times \text{AvgLogoWidth}$
 Replace counted pixels with background color
Endif
5. Count foreground pixels vertically
If Count $> 2 \times \text{AvgLogoHeight}$
 Replace counted pixels with background-color
Endif
6. Store preprocessed image as DP
7. Return DP
8. End

Figure 5 shows the result of preprocessing step. It can be observed that the preprocessed document is free from clutter noise.

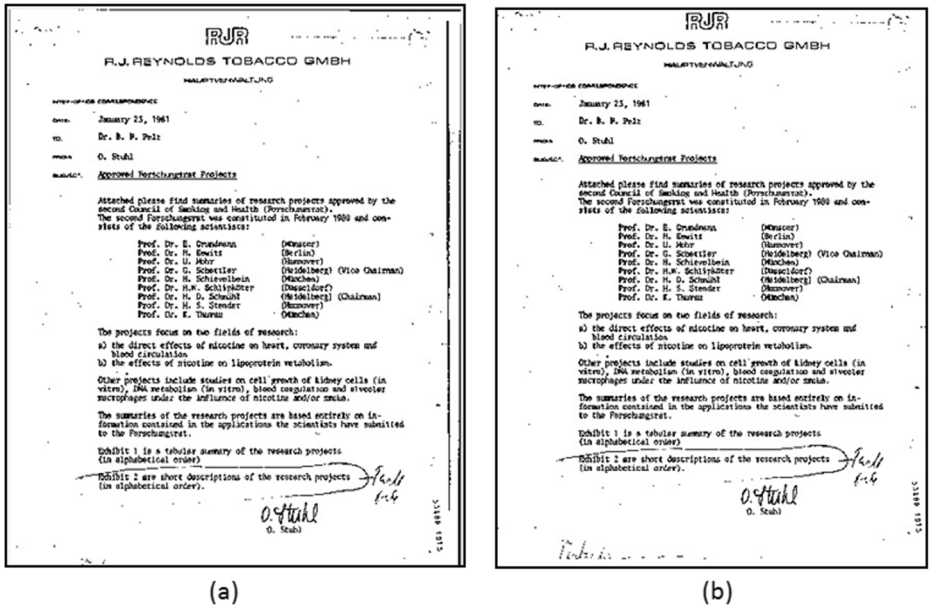


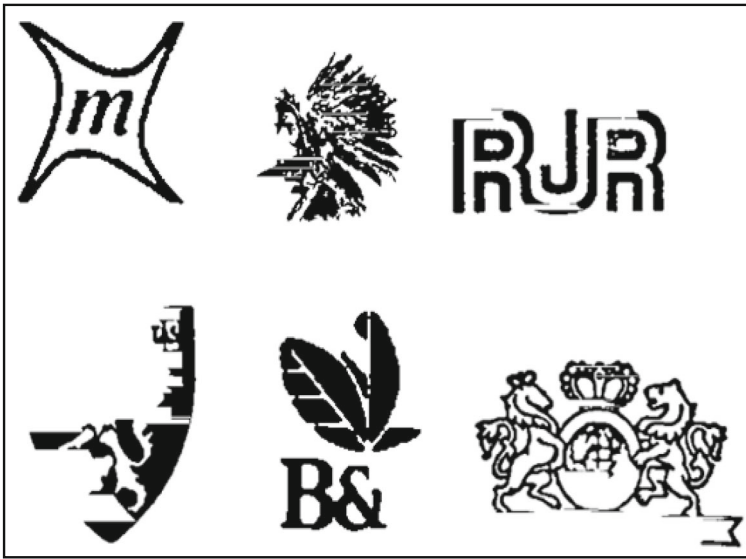
Fig. 5 (a) Input document image (b) Preprocessed document image

3.2 Generating patches of image for training

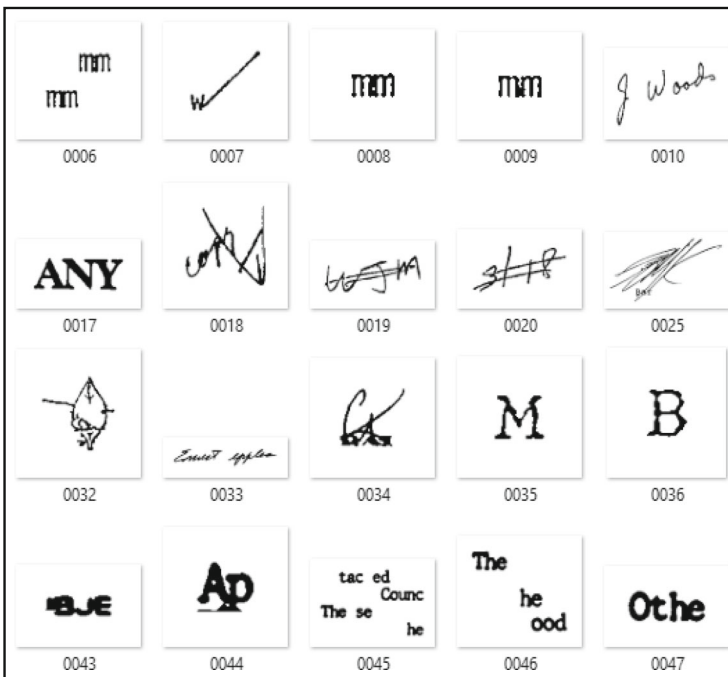
This step is used to generate image patches for training the classifier by analyzing connected components of the document image. The connected component represents a connected set of foreground-colored pixels. We used 30% of the documents for generating the image patches. To reduce the number of image patches for training the classifier, the smallest set of the connected component are discarded because the probability of such components being part of the logo will be very less. Hence the connected components whose size is at least 25% of the largest component in the document are considered image patches in the proposed method. This step has generated 578 image patches, out of which 108 contain logo components and 470 with non-logo components in our experiment. These image patches are used for training the SVM classifier. Figure 6 shows a sample set of logo and non-logo patches. Algorithm 2 shows the procedure adopted for the generation of image patches.

Algorithm 2: Image patch generation for training

1. Begin
2. Input: Preprocessed Document (DP)
Output: Image patches
3. Find connected components of the document.
4. Large=Size of the largest connected component.
5. For each connected component
If size > 0.25× Large
Imagepatch=Connected component.
Endif
6. End



(a)



(b)

Fig. 6 (a) Logo patches and (b) Non-logo patches

3.3 Feature extraction

HOG features have proved their better performance in image analysis, recognition and classification. Hence the proposed method has employed HOG features of the image patches for training the SVM classifier.

Mathematically gradient is the first-order derivative of a function $f(x)$. As an image is a two-dimensional function $f(x,y)$, its gradient can be represented using Eq. (2).

$$\text{Grad}(x,y) = \text{pmatrix} \frac{\partial f(x,y)}{\partial x} \frac{\partial f(x,y)}{\partial y} \text{pmatrix} \quad (2)$$

Where $\partial f(x,y)/\partial x$ is gradient along 'X' direction and $\partial f(x,y)/\partial y$ is gradient along 'Y' direction. In image processing, the derivative function can be approximated to the difference of successive pixel values. Hence we used Eqs. (3) and (4) to compute the gradients.

$$G_X = f(x+1,y) - f(x-1,y) \quad (3)$$

$$G_Y = f(x,y+1) - f(x,y-1) \quad (4)$$

Where ' G_X ' and ' G_Y ' represent gradient along 'X' and 'Y' directions respectively. They produce a difference of pixel values in horizontal and vertical directions respectively.

The magnitude $\text{MAG}(x,y)$ and orientation (x,y) of gradients are computed using the Eqs. (5) and (6).

$$M(x,y) = \sqrt{|G_X^2| + |G_Y^2|} \quad (5)$$

$$(x,y) = \text{Tan}^{-1}\left(\frac{G_X}{G_Y}\right) \quad (6)$$

The procedure for extracting the HOG features includes:

- Dividing the image into cells,
- Organizing cells into blocks of certain size,
- Computing orientation of gradient values for each block,
- Storing the computed values as histograms and.
- Finally concatenating these histograms to generate a feature vector.

In the proposed system, image patches are divided into cells of size 64×64 and organized into blocks of size 2×2 . This results in 9 overlapping blocks per image patch. We used a histogram with 9 bins to store the orientation of gradient values of each block. This resulted in a total of 324 HOG features. Algorithm 3 shows the feature extraction scheme employed for image patches.

Algorithm 3: Feature extraction

1. Begin
2. Input: Image patch (IP)
Output: Feature Vector (FV)
3. Change image patch to a size of 256×256 pixels.
4. Divide the resized image patch into cells of size 64×64 leading to a total of 16 cells.
5. Organize the cells into blocks of size 2×2. This results in 9 overlapping blocks.
6. Compute Orientation of gradient values for each block and store them using 9 histogram bins.
7. Concatenate the histogram of gradient values of each block and store them in a feature vector FV.
8. Return FV.
9. End

3.4 Logo detection

The logo detection procedure involves accepting the input document image, finding connecting components and detecting the component that comprises the logo using an SVM classifier. As the goal is to classify components as either a logo or non-logo, the binary SVM is used in this step. The SVM works on the principle of a hyper-plane to separate the data points into two groups for classification. The optimal hyperplane is given by Eq. (7).

$$OHP = W^T(x) + b \quad (7)$$

Where ‘W’ indicates the normal vector, ‘b’ indicates an offset vector of the hyperplane with the kernel function (x). Algorithm 4 shows the procedure adopted for the detection of a logo.

Algorithm 4: Logo detection from the input document

1. Begin
Input: Document Image
Output: Detected logo
2. Find the connecting components.
 - <For each component>
 - if size > 0.25×LargestComponent
 - check whether the component is logo or not using trained SVM classifier.
 - if connected component is logo
 - DetectedLogo=connected component
 - goto step 3
 - endif
 - endif
 - <Endfor>
3. Return DetectedLogo
4. End

4 Results and discussion

The proposed system is evaluated using the Tobacco-800 database [30], which is publicly available. This dataset includes 1290 document images with a resolution of 150 to 300 DPI. The dimension of these images varies from 1200 to 1600 to 2500 to 3600 pixels. These document images are produced by using different types of equipment over a period of time. It is the popular database used to evaluate many document image analysis algorithms and content-based retrieval of documents by researchers. For experimentation purposes, we have considered the documents comprising logos and divided these document images into 9 categories, each category consisting of a unique logo. A total of 295 document images, each category consisting of minimum 6 documents to 54 documents are used for experiments in this paper. Figure 7 shows the sample results of logo detection along with input documents.

The performance of the proposed system is assessed using the parameter logo detection rate. It is computed using the Eq. (8).

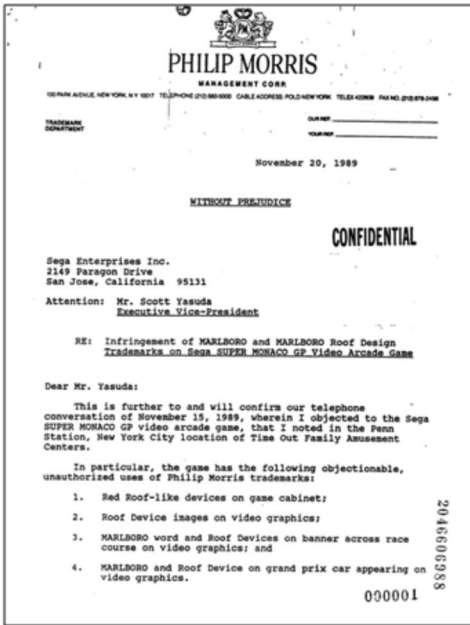
$$\text{Logo detection rate} = \frac{\text{Correctly detected logos}}{\text{Number of document images}} \quad (8)$$

The detection rate for each category is computed and also compared with earlier methods. Table 2 provides the details of logo categories, the number of document images considered for evaluation, the logo detection performance of earlier techniques and the proposed method.

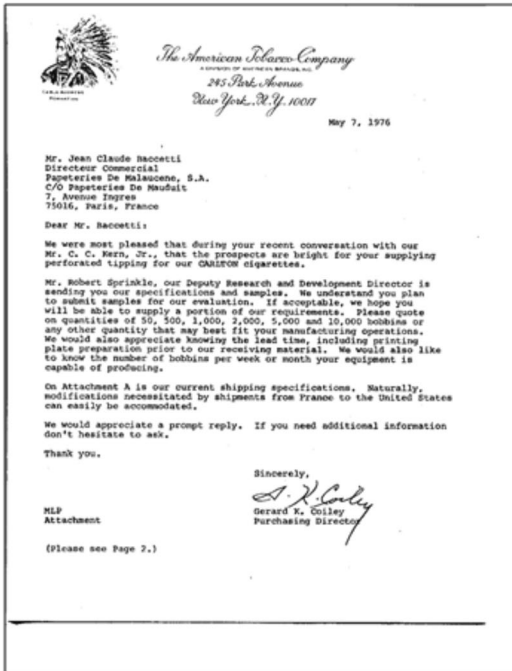
Figure 8 shows the graphical comparison of the detection rate obtained for 9 categories of logos listed in Table 1. It can be observed that the proposed system provided a better logo detection rate for all 9 categories. To comprehend the performance of the proposed system we have taken the average detection rate of these 9 categories of logos also into consideration. Figure 9 shows the comparison of the average detection rate obtained with the proposed method and other techniques. This comparison shows that the proposed method has also improved the performance of the average logo detection rate by approximately 5%.

5 Conclusions

Logo detection plays an important role in logo recognition, logo matching and logo-based document retrieval. This paper presented an efficient logo detection method for the automatic extraction of logo candidates from the document image. HOG features of connected components and the SVM classifier are employed with a set of preprocessing operations to implement the proposed method. Experimentation is conducted on the publicly available database Tobacco 800. The proposed method outperforms in comparison with existing methods. The proposed technique can also be used with machine learning and deep learning algorithms to have improved performance.



(a) Sample Result 1 (Input Document and Detected Logo)



(b) Sample Result 2 (Input Document and Detected Logo)

Fig. 7 Sample results of logo detection. (a) Sample result 1 (Input document and detected logo). (b) Sample result 2 (Input document and detected logo)

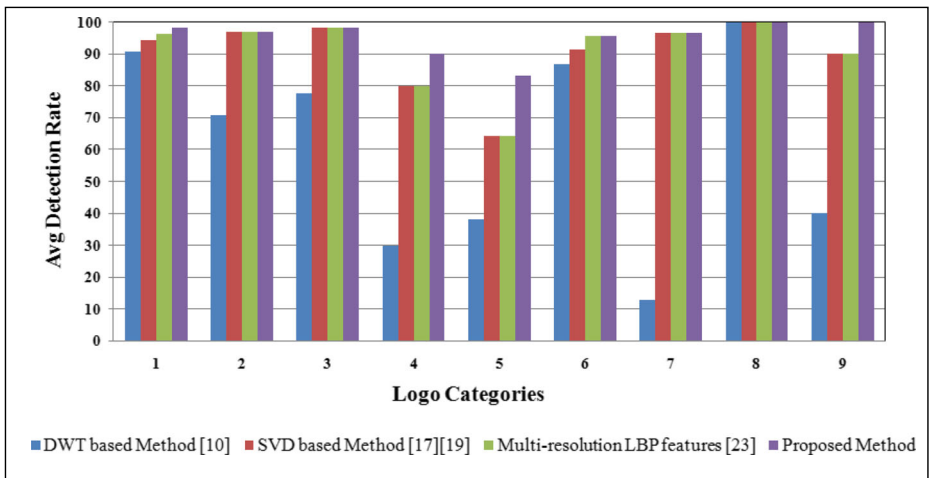


Fig. 8 Logo detection rate for different categories of logos

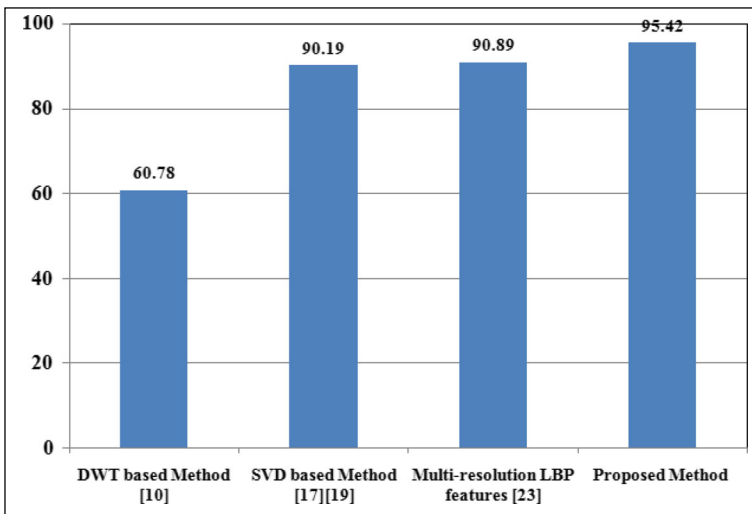


Fig. 9 Graphical comparison average logo detection rate

Declarations

Conflict of interest The authors declare no conflict of interest.

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