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Survey

Logo and seal based administrative document image retrieval: A survey

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ABSTRACT

With the advance of technology, business offices and organizations together with their clients create a massive amount of administrative documents every day. Administrative documents commonly contain some salient entities such as logos, stamps or seals as the means of their authentication and proprietorship. These salient entities provide quite discriminative information, which can effectively be used for different tasks of document image retrieval, classification and recognition in document-based applications. Thus, proper detection/recognition of these entities in document images increases the performance of such applications in terms of document retrieval, classification, and recognition. To present the state-of-the-art research on the retrieval of administrative document images, this paper deals with a survey of administrative document image retrieval in relation to seals and logos. All the available datasets, feature extraction and classification techniques for logo and seal detection/recognition are discussed systematically. The shortcomings of the present technologies on logo and seal based document processing are also highlighted. Avenues of the future works are further given for the benefit of readers. To the best of authors' knowledge, there is no survey on administrative document image retrieval and hence the authors hope that this work will be helpful to the researchers of the document analysis community.

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Contents

1. Introduction	48
2. Properties of logo and seal	49
3. Overview of an administrative document image retrieval/classification system	50
4. Related works on logo and seal	51
5. Detection methodologies	52

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5.1.	Techniques for detection of logo in administrative documents	52
5.1.1.	Connected component based approaches	52
5.1.2.	Window-sliding (block) based approaches	52
5.1.3.	Detection based on recognition approaches	52
5.1.4.	Techniques based on local descriptors	52
5.1.5.	Logo detection results and discussion	53
5.2.	Techniques for detection of seal in administrative documents	53
5.2.1.	Techniques based on color information	53
5.2.2.	Shape/graphical based approaches	53
5.2.3.	Techniques based on textual information	55
5.2.4.	Seal detection results and discussion	55
6.	Recognition methodologies	55
6.1.	Related methods for logo recognition	55
6.1.1.	Features used for logo recognition	55
6.1.2.	Classifiers used for logo recognition	56
6.1.3.	Logo recognition results and discussion	56
6.2.	Related methods for seal recognition	58
6.2.1.	Seal identification	58
6.2.2.	Seal verification	58
6.2.3.	Seal verification/recognition results and discussion	59
7.	Benchmarks and available datasets	59
8.	Discussion and remarks	59
9.	Conclusion and future directions	60
	References	61

1. Introduction

With the advance of science and the prevalence of electronic media in every step of daily life, the need for transforming different information in the form of documents into electronic format is increasing day-by-day. Furthermore, digital born documents are also increasing rapidly. Libraries and archives are generally interested in mass-digitization and transcription of their collected books and resources. Administrative, communication and filing procedures, which were mostly paper-based, are driven into a digital environment by the ubiquity of different computation facilities. In all these applications, the objective is not only to preserve documents in a digital format, but also to process documents to provide an easy access and retrieval service to a wider number of users. Traditionally, document retrieval is associated to textual analysis. The records in typewritten and structured documents are indexed with the use of a traditional high performing commercial Optical Character Recognition (OCR) product. Once the document image is OCRed/indexed, the resulting ASCII information is compared to the query using a string-matching algorithm [1]. However, the OCR generally fails to perform accurately on the documents with a high degree of degradation, such as fax and scanned documents. Recently, many systems and technologies have become available to comprehend huge volume of electronic documents and to handle such type of documents [2–4,1]. In general, Content Based Image Retrieval (CBIR) is one of such technologies employed in a wide range of applications. Content-based Document Image Retrieval (CBDIR) is a subdivision of CBIR, where large-scale document retrieval is performed according to a users' request. CBDIR involves a search process, where the user's request is a model or a concept to be found [3,1].

Public organizations, institutes, companies and private sectors are generally interested in implementing digital mailrooms to improve the efficiency of paper-intensive workflows and to reduce the burden of manual processing of different administrative documents including incoming mails, faxes, forms, invoices, reports, employee records, health record, etc. By this digital mailroom, public and private sectors would obviously like to have an automatic indexation of their incoming documents that results in automatic classification, distribution, and also easy access and retrieval of those documents in future. As mentioned, one possible solution is the use of textual information for automatic indexation of those administrative documents. However, besides the presence of textual information, administrative documents commonly contain different salient entities such as logos, stamps/seals, layout-structure, signatures, and bar-codes, which refer to the paradigm of corresponding organization, institute, product or personnel. These salient entities have a rich context information providing distinctive features and characteristics to deal with the problem of document image analysis. Truly speaking, these salient entities have mainly been considered as an alternative pathway for administrative document image retrieval (ADIR) and document classification.

Logo and seal can be considered as two important and popular salient entities presented in administrative documents. The manual identification/verification of logos/seals is not an easy task, as the documents in-flow in organizations is growing rapidly. Therefore, many research works have been carried out to automatically detect and verify logos/seals facilitating such administrative document-based systems. Indeed, accurate detection and recognition of logo/seal in document images provide us with a more reliable and appropriate system.

However, logos and seals detection/recognition is a challenging task, as logos and seals are generally composed of quite complex symbols, graphical and textual components. Presence of noise and degradation make the detection/recognition task more difficult. There are also some specific issues related to logos and seals that make the detection/recognition more challenging. For instance, seals may be affixed in any orientation at different locations within an administrative document. In addition, seals sometimes contain unpredictable patterns due to imperfect ink condition, uneven surface contact, noise, etc. Overlapping of seals with text/signatures, and missing part of a seal are other typical problems included in seal detection/recognition task [1].

Considering the related literature of logo/seal detection/recognition/retrieval in document images, it may be noted that research in this particular domain has gradually been evolved from the task of logo/seal recognition to the task of logo/seal detection [5–8]. However, in a general problem of administrative document retrieval, detection step might take place before or along the recognition step [9,10]. Therefore, in this paper, we first review the techniques that belong to logo and seal detection and then discuss the methods presented for the recognition purposes.

The rest of the paper is organized as follows. In Section 2, some specific characteristics of logos and seals are drawn. In Section 3, an overview of a general system for an administrative document image retrieval system is described. Related works in relation to logos or seals as the main devices for detection, retrieval, classification and recognition are reviewed in Sections 4–6. Benchmarks and datasets used for experimentation and comparison analysis are presented in Section 7. Discussion and remarks are provided in Section 8. Finally, conclusion and future directions are drawn in Section 9.

2. Properties of logo and seal

A logo is a unique sign used by a company, institute, organization or an individual to identify its products or services to consumers. Furthermore, a logo can help customers to remember an organization's name or a trademark. A logo may be composed of completely graphical or textual or both graphical and textual components. Some instances of such logo types are shown in Fig. 1. Although logos can be found in many styles, but they are bounded by a certain design constraint as they need to be salient and easily identified by human beings. The text in a logo is often modified for its aesthetic appealing and as a result, its segmentation for the OCR processing may not be easy. Thus, the text can be viewed as a part of the logo, which needs to be handled with other graphical components by a general shape analyzer. Similarly, if a logo contains texture patterns, the texture patterns can be treated as a graphical pattern and, again, can be handled with other logo components together [11]. Since a logo may be designed with a few setting of color combinations, color information may be used for logo detection/recognition. Colors may sometimes be ignored as far as the unique identity of a logo (represented as an intrinsic graphic pattern) is concerned [9]. Trademark image retrieval (TIR) is a branch of CBIR [12] and many studies

have been carried out in this particular area. Review of techniques related to trademarks is out of the scope of this review paper and is not included here.

Seal as another entity in administrative documents is a device for making an impression in paper, wax, clay, or some other medium. Seal imprints are widely used for personal or organizational identification. Seal imprints appear on many types of documents such as bank checks, receipts, proposals, and money withdrawing slips. Their presence proves the authenticity besides providing some vital information about such documents. Correct identification of seals in administrative document images plays a pivotal role in verifying the identities and the corresponding authorities that sealed those documents [13].

Seals may contain both textual and graphical components. A seal is manually set inside a document after immersion in an inkpad. Seals generally have a closed connective contour surrounding text characters, and graphical components inside the seal. They bear some constant character strings to convey information about owner/organization, usage and its locality. Besides, in many instances, a seal contains a variable field of index number, date, etc., which may indicate sending or receiving date of a document [14]. Three seals with different characteristics are shown in Fig. 2.

From the definition and properties of logos and seals, one may note that the logo and seal are very similar in terms of definition, visual appearance, etc. Both logo and seal can also be used as the means of authentication/verification. However, there are many differences between logos and seals in terms of geometrical positioning, presence of variable field, etc. A summary of similarities and dissimilarities between logos and seals from different aspects is provided in Tables 1 and 2, respectively. From Table 1 it is evident that logos and seals can be composed of color, textual, graphical or both textual and graphical components. As demonstrated in Table 2, logos generally appear on a specific position at the very top (or rarely at the foot) of official papers/forms of companies/institutes in already printed format, whereas seals are manually put beside signatures of administrative authorities at the middle/bottom of documents/letters at the time of generating the documents before dispatching them. Moreover, seals may be imprinted using varieties of ink colors and imprinted qualities of seals may differ due to different physical pressures of different imprinters.

It is worth mentioning that logos and seals are quite different from other graphical entities such as charts, electrical/architectural symbols, drop caps and character images. Logos and seals are generally complex entities composed of graphical symbols, characters, etc. Moreover, seals and logos bear some structure meaning to convey some information about the organizations' owners and their locality to the observers/clients/receivers. In contrast, other graphical entities do not have such properties. Logos and seals need to be affixed at some places to be easily distinguishable by receivers/clients. Other graphical entities cannot be used for such purposes. These properties and differences make logos and seals totally distinctive from other graphical entities.

Considering the properties, a priori knowledge and also significant differences between logos and seals, different types of features have been employed to describe those



Fig. 1 – Three different types of logos: (a) A graphical logo, (b) a textual logo, and (c) a logo composed of both textual and graphical components.

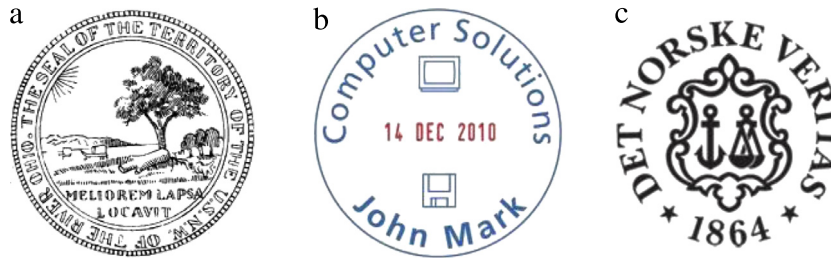


Fig. 2 – Three different types of seals: (a) A seal composed of graphics and text surrounding by a closed contour, (b) a seal composed of a date field in middle, and (c) a seal without a closed contour at its surrounding.

Table 1 – Similarity in terms of characteristics of logos and seals.

	Presence of color	Presence of textual part	Presence of graphical part	Presence of both textual & graphical parts	Does it use for authentication	Scale free with respect to a paper
Logo	Yes	Yes	Yes	Yes	Yes	Yes
Seal	Yes	Yes	Yes	Yes	Yes	Yes

Table 2 – Dissimilarity of logos and seals.

	Position	Imprinted	Pre-printed	Use of ink color	Presence of variable field	Rotation free with respect to a paper	Translation free with respect to a paper
Logo	Top/bottom	No	Yes	No	No	No	No
Seal	Any where	Yes	No	Yes	Yes	Yes	Yes

characteristics of logos and seals in the respective logo/seal detection/recognition/retrieval literature [15–19,10]. Details of features and different stages used to handle the problem of logo and seal detection/recognition/retrieval in document images are illustrated in the subsequent sections.

3. Overview of an administrative document image retrieval/classification system

Block diagram of a general ADIR system is depicted in Fig. 3. As demonstrated in Fig. 3, preprocessing, feature extraction, spotting and matching are four main steps of an ADIR system. In any logo/seal based ADIR, the most challenging task is localization (spotting) of logos/seals in document images. In case of obtaining accurate logo/seal localization, recognition/classification/retrieval is an easier task compared to the logo/seal detection/spotting task. Compared to a general CBIR problem an ADIR system has two distinct

characteristics as: (i) since logos/seals are complex entities, logo/seal based ADIR is more challenging problem compared to the CBIR applications, and (ii) in an ADIR system, domain/a priori knowledge about logo/seal models, document images types, documents layouts, and context information can be used at different steps of the system, whereas in a general CBIR, these information may not be available.

Pre-processing as a primary step in any CBIR system is employed to enhance the quality of image for further processing. Especially when image is corrupted by noise, bad illumination, blurred, and skew/slant, pre-processing is necessary to enhance the image quality. Pre-processing usually includes filtering, skew correction, normalization and segmentation. Filtering methods are commonly employed on input images to enhance the appearance of the images either for visualization purposes or for further image processing tasks. Examples of some image enhancement filters are: mean filter, low pass filter, high pass filter, Gaussian filter, anisotropic diffusion, histogram equalization,

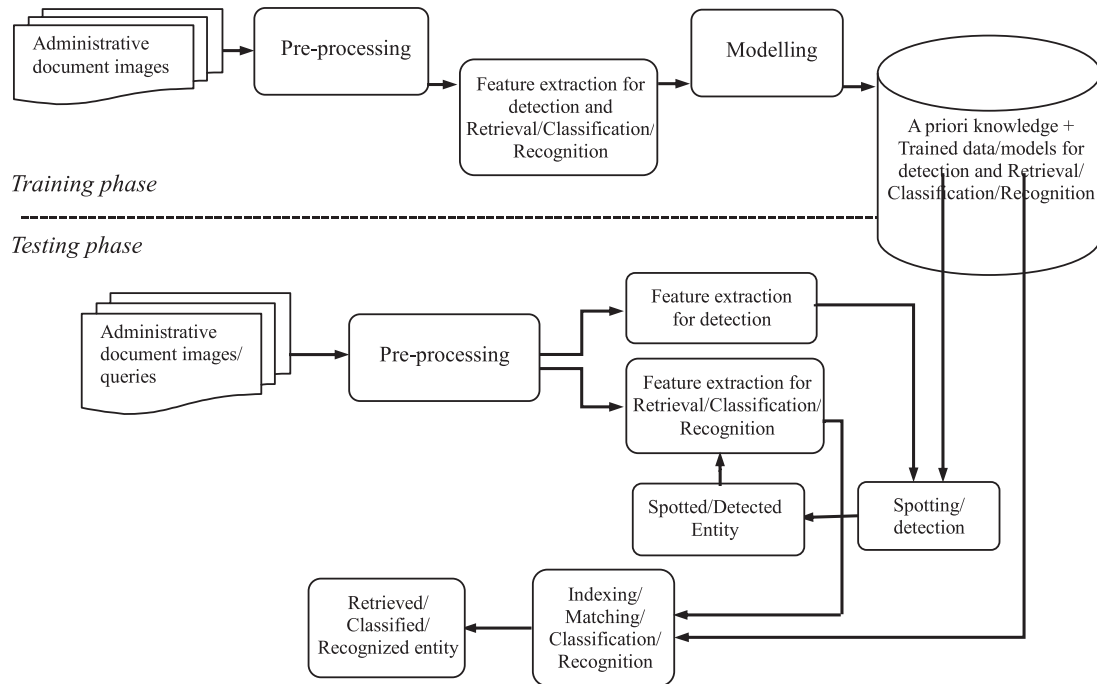


Fig. 3 – An overview of a general administrative document image retrieval/classification/recognition system.

etc. Normalization is generally referred to either changing the image size or normalizing the features extracted from an image [20].

With reference to logo/seal based administrative document image applications, skew detection/correction and filtering are quite effective preprocessing techniques used for improving logo detection/recognition results [21].

Segmentation is generally used to obtain some regions of interest in order to provide object level access in an image [20]. However, segmentation process is a challenging task, as it is difficult to automatically determine an appropriate level of segmentation for a particular task. Segmentation is also an error-prone process that results in over or under segmentation results.

In logo and seal based ADIR systems, many discriminating features have been used to construct a meaningful descriptor for different logo or seal models. The descriptors are used for the detection/spotting and/or retrieval/classification purposes. Based on different sources considered for feature extraction, features can be categorized into three groups: (i) low-level features, (ii) middle-level features, and (iii) high-level features. Low-level features are extracted from a pixel or from a group of pixels. Middle-level features are extracted from blobs or regions extracted from image segmentation results. High-level features are semantic information that represents an image by objects that it may contain. They subsequently help to classify the image to which the image belongs. Since one type of features can only represent a part of the image properties, combination of features has also been employed to improve final detection/recognition/retrieval result [22,20].

Spotting can be defined as localization of a given query of a salient entity such as a logo, a seal, or a symbol in a large

collection of document images. Possible application of logo or seal spotting is retrieving invoices of a particular provider from a large database of documents by querying the logo or seal of a company/provider. Spotting methods in general rely on various pattern recognition methods including signatures, Radon transform and structural approaches of which the structural approaches are powerful in terms of representational capability [23,17,18,20].

Similarity matching involves feature-matching to obtain a visually similar entity amongst a group of samples that belong to different classes. A commonly used similarity measure method is the distance-based method. Different distances such as Euclidean distance, City Block distance, Canberra distance are frequently used in the literature for computing distance between features. A retrieval or classification system generally retrieves and presents a sequence of images ranked in a decreasing order of similarity or the one with the minimum distances is returned to the user as the most similar class or class label of the input sample [22,20].

4. Related works on logo and seal

The problem of using logo/seal information for document image processing basically involves two main tasks: (i) finding boundary of a logo/seal on a document image irrespective of its class, and (ii) indexing/matching the detected logo/seal candidate region to a database for classifying or for concluding that the region is not of interest. The former is referred to as logo/seal detection/spotting, while the latter is called logo/seal recognition. Logo/seal retrieval can be viewed as a combination of two problems that one wants to simultaneously detect and recognize a logo/seal across

a dataset based on a query image [24]. Considering these two tasks, the literature review related to logo and seal may also be divided into (i) logo/seal detection, and (ii) logo/seal recognition. In relation to the evolutionary aspect of the technology, the recognition step has been started earlier than the detection step [25,17,18,13,26–29,19,30–35]. However, to respect the continuity of the presentation in this paper, first, the techniques developed for logo/seal detection are discussed and then methods for logo/seal recognition are overviewed.

5. Detection methodologies

5.1. Techniques for detection of logo in administrative documents

A number of techniques have been proposed in the past for logo detection [36,24,8,37,21,15,16,38,9,25,17,18,39,40,10]. These techniques can be categorized into four main groups: (i) connected component based approaches, (ii) window-sliding (block) based approaches, (iii) detection based on recognition approaches, and (iv) techniques based on local descriptors. In the following subsections a review of the logo detection methods based on this categorization followed by results and discussion is provided.

5.1.1. Connected component based approaches

In the connected component based techniques [36,8,21,38,25,17], initially, a document image is binarized. Then connected component labeling process is performed to obtain a list of connected components from the binarized image. Next, various features (width, height, aspect ratio, area, density, etc.) are computed to characterize each extracted connected component (CC). These features are used along with some classifiers (decision trees) to discriminate non-logo from logo components. Since, CCs may be fragmented or touched due to noise, etc.; CC based approaches are very sensitive to the quality of document images and binarization. To overcome the problems that occur due to the use of CCs analysis method, some alternative approaches have been investigated in the literature. In [8], using concept of anchor line a geometrical reconstruction method has been proposed to ensure the geometrical relationship among the features computed from connected components. In the system presented in [21], logo localization has been performed by grouping the CCs using similarity and neighboring criteria. A similar process has been presented in [36], and different parts of a logo have been grouped using vertical centroid coordinates and overlapping of bounding boxes obtained from different parts of the logo. Feature rectangles, which are minimum rectangles that fully embrace at least one foreground pixel, extracted from CCs have also been used for logo detection in [25]. Using a binary tree and based on the position of feature rectangles, width, height and aspect ratio of feature rectangles, logos and non-logos have then been discriminated [25]. In [17], a multi-scale boosting strategy based on Fisher classifiers at different levels has been employed to distinguish logo and non-logo components. The approach is a segmentation free and layout independent

approach. A number of features, such as aspect ratio, area, spatial density and context distance (distance between a region and the center of logo's clusters), have been used to characterize logo and non-logo components.

5.1.2. Window-sliding (block) based approaches

In the second category of logo detection techniques local detectors/descriptors, such as density, probability and blurred shape, have been used [37,15,39,10]. These descriptors have been computed from the regions of interest or patches extracted based on a sliding-window or a segmentation technique. In [37], following the binarization step, mountain function has been computed for each window to capture the spatial density of foreground pixels in each window. Using the extracted spatial density features and a decision tree, a window has been classified either as a part of a logo or a non-logo. The work described in [15] is based on computing Blurred Shape Model (BSM) descriptors as features and employing normalized cross-correlation between BSM of logo model and BSM of document image as detection strategy. In this technique, probability of pixel densities in image regions has been encoded for detecting the most probable logo region. In [39], mathematical morphology operators have been employed to decrease the distance between the identical logo parts. Graphical regions have been separated from the text regions using spatial and chromatic densities, shape, location and number of sub-regions (components). In [10], at the coarse level of the proposed scheme, content of a document image has been pruned utilizing a decision tree and a small number of features such as frequency probability (FP), Gaussian probability (GP), height, width, and average density computed for patches extracted employing the piece-wise painting algorithm (PPA). At the fine level, the detected patches have been refined integrating shape context descriptors and a Nearest Neighbor (NN) classifier [10].

5.1.3. Detection based on recognition approaches

A unified framework for detection and recognition of logos in document images has been proposed in [9], which can be considered as a new category of logo detection techniques. In this work, the authors have used feature rectangles and Region Adjacency Graph (RAG) to model logos. The final detection/recognition has been derived using a Bayesian network classification, which provides feedback to the detection stage for appropriate pruning and merging the nodes of the RAG. For the recognition of logos, a unique set of global and local geometric invariants (moments, elongation and invariant signature curve) has further been computed for each logo.

5.1.4. Techniques based on local descriptors

In proposed systems based on local descriptors [24,16,18,40], at first, local detectors such as Hessian [24], Harris–Laplace [16], Difference of Gaussians (DoG) filter [41], Canny edge and He & Yung detectors [18] are computed at pixel level to extract a set of key points. The key-points are then exploited by local descriptors such as Shape Context (SC) [16,18,40], Scale-Invariant Feature Transform (SIFT) [15,16,41,42], Binary Robust Independent Elementary Features (BRIEF) [41] and Speeded Up Robust Features (SURF) [24].

In [16], logos have been described by a set of SIFT descriptors. The document classification has been performed by the use of a bag-of-words model. Spatial coherence rules have been added using an open morphological operation to reinforce the correct category hypothesis. In [18], logo detection/segmentation has been performed boosting a cascade of classifiers across multiple image scales. Then logo matching has been accomplished using a translation, scale, and rotation invariant shape descriptors. In [15], two techniques based on SIFT and blurred shape descriptors for the classification of documents have been presented. To reduce computation time, just upper parts of documents have been considered for the processing. The blurred shape descriptor has shown better performance on documents containing graphic rich logos, whereas, the SIFT descriptor has shown better performance on documents having mostly textual logos. A logo spotting and matching method based on key-point detection and SIFT descriptors has been proposed to retrieve document images in [41,42]. Key points have initially been filtered by the nearest neighbor matching rule [41] and have then been post-filtered with homography using RANSAC [41] and BRIEF descriptor [42].

5.1.5. Logo detection results and discussion

To have an overall overview of the techniques proposed for the detection of logos in document images a brief description of each technique is provided in Table 3. As demonstrated in Table 3, most of the methodologies in the literature for the logo detection have been conducted on the Tobacco-800 dataset [43]. Among the CC-based logo detection systems the method presented in [8] has provided considerably encouraging results, however, the CC based methods for logo detection are generally sensitive to noise, degradation, scale variation and skew. In the second category of logo detection methods, the method presented in [37] has shown quite interesting results. Nevertheless, concerning subjective idea of logo detection, the method presented in [37] is zone classification rather than logo detection. Regarding the uniformity of detection and recognition in a single framework with the use of a feedback strategy, the method presented in [9] is the best example in the literature for logo detection/recognition. In case where the use of a priori and domain knowledge is affordable, the systems proposed in [21,17,18,20] can be good choices to deal with the problem of logo detection/recognition. In terms of color/gray document images the method based on bag-of-visual-word and key point detection [24,8,15,16,41,42] and matching can be well adapted to the problem. Moreover, most of the methods are invariant to image transformations. The techniques based on SIFT and SURF are also segmentation free techniques [24].

In relation to time complexity of the logo detection methods in the literature, it is noted that the time complexities of most methods are of linear complexity ($O(n)$ or $O(kn)$, where k is a small constant value) that makes those methods suitable for practical applications.

5.2. Techniques for detection of seal in administrative documents

There are few pieces of work on seal detection in document images in the literature [44]. Considering the properties of seals represented in Tables 1 and 2, color [45,46], shape/graphical [47], and textual information [1,48] of seals have been explored for seal detection/spotting in administrative document images. A brief review of seal detection methods in the literature along with their results is provided in the following.

5.2.1. Techniques based on color information

Color information can help in distinguishing seal objects from other parts of documents. As color is generally used in seal imprint, color segmentation algorithms have been used for seal detection in [45,46,49]. A fuzzy integral based technique, which selectively extracts color clusters in images, has been presented in [45]. Two different fuzzy integrals namely, Choquet and Sugeno have been used for seal isolation [45]. RGB color analysis has been employed to first localize candidate color seals in document images [49]. Candidate seals were further analyzed using contour information. A contour localizer (e.g. ellipse, circle, rectangle, etc.) has finally been used to detect the template seals in document images. In [46], a technique for isolation and verification of seals and signatures in Japanese bank-checks using color images has been proposed. In the first step, the RGB color space of the input document image has been converted into the HSV color space. Next, the document image colors in HSV color space have been clustered for isolation of identical color components in the input image to localize/find seal presented in the input document image [46].

5.2.2. Shape/graphical based approaches

The boundary shapes of seals (e.g. circular, rectangular and elliptical) have also been used for seal localization in document images [47]. In this type of approach, generally a prior knowledge about outer boundary shapes of seals has been taken into account for seal localization at the coarse level [47]. The connected edge patterns have been used to analyze the shape contours of a seal in [27]. Detection of seals has been achieved by employing a method for finding ellipses in binary document images. It has been reported that about 2–3 s were needed to detect a seal in an image of 2000 * 2500 pixels [27].

In [50], a technique based on run length smoothing has been presented for seal extraction in an Indian Postal System. After applying a run-length smoothing algorithm on a binary image, the image has been divided into a number of small blocks. Based on the pixel density and the number of connected components present in each block, seals/logos have been separated from the other parts of postal mail images. Some prior information about the position of seals has further been utilized to improve seal detection process [50].

An automatic template generation algorithm was used for finding each category of seals from historical postcard images [51]. Postmarks/seals were detected using circle detection analysis and cascaded unsupervised learning. Agglomerative hierarchical clustering was used to obtain 377 clusters from 581 samples.

Table 3 – The results reported based on different techniques for logo detection in the literature. Here T, R and S denote translation, rotation and scale properties respectively. Y and N are also used as the means of “Yes” and “No”.

Method	Features	Invariant to image transformation			Dataset	No. of images	No. logos	Training dataset	Testing dataset	Precision (%)	Acc. (%)	Time complexity
		T	R	S								
[24]	SURF features	Y	Y	Y	Tobacco-800	435	NA	NA	87	NA	NA	$O(n^2)$
[8]	Local descriptors, convex hull, direction	Y	Y	Y	Tobacco-800	1290	50	365	365	99.4	86.5	$O(m)$
[37]	Foreground spatial density	Y	Y	Y	Tobacco-800	1290	100	316	316	32.1	39.3	$O(m)$
[21]	Contour based features	Y	N	Y	Tobacco-800	1290	50	1240	1240	44	91	$O(kn)$
[21]	Contour based features	Y	N	Y	Tobacco-800	426	50	376	376	92.98	90.05	$O(kn)$
[38]	CC based features	Y	N	Y	UMD	255	35	220	220	NA	88	$O(m)$
[9]	Moments, contour features	Y	N	Y	Tobacco-800	400	100	300	300	94.7	84.2	$O(m)$
[25]	Feature rectangles	Y	N	N	Tobacco-800	416	435	100	316	93.3	80.4	$O(kn)$
[17]	Context distance	Y	Y	Y	Tobacco-800	1290	432	50	1240	73.5	84.2	$O(kn)$
[18]	Shape descriptors	Y	Y	Y	Tobacco-800	1290	432	432	386	82.6	78.5	$O(2 \log n)$
[10]	Probability, Gaussian features	N	Y	Y	Tobacco-800	1290	432	100	316	75.25	91.50	$O(kn)$
[41]	Local descriptors	Y	Y	Y	Tobacco-800	1290	432	432	1240	91.15	88.78	$O(2n + \log n)$
[42]	Local descriptors	Y	Y	Y	Tobacco-800	1290	432	432	1240	97.67	95.86	$O(2n + \log n)$

5.2.3. Techniques based on textual information

There are few works based on textual information for seal detection. In [48], a template cross-correlation based technique, which exploits the existence of some constant character strings, has been employed at the initial stage of seal detection. Topology of detected character instances has then been considered to remove the false positives from the actual seal components [48]. A (character) recognition-based strategy has been proposed for scale and rotation invariant seal detection in [1]. Initially, extracted CCs (characters) have been labeled using a rotation invariant feature descriptor and Support Vector Machine (SVM) classifier. Then, the Generalized Hough Transform (GHT) concept following a voting scheme has been applied to find possible location of a seal in a document based on the spatial feature descriptor of component pairs [1]. The methods presented in [27,48,50] can fairly be called as detection based on recognition approach, since, they have used some recognition strategies at different stages for the detection purposes.

5.2.4. Seal detection results and discussion

The techniques used for seal detection in document images are briefly outlined in Table 4. From Table 4, it may be noted that color information has widely been exploited for seal detection, whenever seals and document images appear in different colors. In two-tone images generally seal images have been treated as whole symbol and in such cases pattern recognition techniques such as shape analysis and textual properties in seal [1,48,47,52] have been used. Though, a few papers mentioned the accuracy of their approaches, it is to be noted that due to variability of seal images and qualities in respective datasets, the performance evaluation may not be comparable.

6. Recognition methodologies

Logo/seal identification can be regarded as an application of the general pattern recognition schemes. Alike any other pattern recognition systems, the problem of logo and seal recognition generally involves three vital tasks: (i) preprocessing, (ii) extracting meaningful features for a logo/seal, and (iii) classifying/indexing a detected/spotted logo/seal into a large database of logos/seals or a database of documents which contain logos/seals [5]. A critical assumption in most of the recognition strategies presented in the literature is the availability of logos or seals provided by manual segmentation. Pieces of works related to logo and seal recognition are reviewed below.

6.1. Related methods for logo recognition

In document image analysis applications, two analogous logo recognition tasks are of interest. First, given a document, which contains a logo, classify the logo as one of a finite set of known logos in a logo database or conclude that the logo does not present in the database. Second, given an extracted logo (known or unknown), index a database of documents and extract all the documents, which contain the extracted logo. Both problems can be viewed as indexing into

a possibly large database of logos or documents based on features extracted from logos or candidate logo regions [5]. In both cases a primary logo detection procedure is necessary to provide the required information for logo recognition. In literature, there are many research works for the recognition of logos [35] and trademarks [12,7,53,22,23,4]. Since trademark recognition is relatively close to the logo recognition problem, a few papers from trademark recognition literature are also reviewed here. From the literature of logo recognition techniques, it is evident that most of the techniques considered logos as entities perfectly segmented from the documents [35]. In this case, two main steps of feature extraction and then classification are commonly employed for logo recognition in the literature [35]. For the sake of clarity, the same pipeline used in the recognition process is followed in this paper to review the logo recognition methods in the literature. The logo recognition results obtained in the literature are also reported.

6.1.1. Features used for logo recognition

To characterize logos, researchers have utilized different feature extraction techniques in the literature. Based on the type of features and descriptors used for the recognition purpose, logo recognition techniques may be categorized into two main groups: (i) statistical logo recognition, and (ii) structural logo recognition.

In the statistical approach, different kind of information such as geometric information, statistical moments and image transformations have been used in the literature for logo recognition. In structural based techniques, primitives and geometric relationship among them have also been considered for logo recognition. Graph representation is such a technique, where the recognition task is defined as a problem of sub-graph matching. Some other methods such as Shape Context, SIFT and SURF based approaches exploit spatial interrelation features to describe regions and contours in order to characterize logos [3].

From the perspective of local/global representation/characterization of a shape, features can be categorized into two main groups: (i) local features and (ii) global features. Local features are summarized according to their extraction for each point of input domain, whereas global features are extracted based on sets of pixels, on a region or even on the whole document. Based on this categorization outline, local features used for logo recognition include: features extracted from local zone [54], differential invariants [5], negative shape features [6], primitives (line segments) [55], curvature and distance from centroid point [12,7], SIFT and SURF descriptors derived from Hessian-affine interest points [56–58], horizontal gaps per total area, vertical gaps per total area, ratio of hole area to total area [59,60], color [61], Delaunay triangulation of components/local features [61,60], bag-of-words features [60], edge based features extracted using GHT [62], Fourier coefficients of segmented boundary curves [63], rectangle features extracted from integral image [64], etc.

Global features utilized in literature for logo recognition are: different moments (Zernike, Tchebichef, invariant, radial) [54,11,59,65,2,7], projection profiles [66], bispectral [66], gradient features extracted from contour points [67–69], algebraic invariants [5], wavelet-based features [6,70], circularity,

Table 4 – The results reported based on different techniques for seal detection/segmentation in the literature.

Method	Feature	Invariant to image transformation			Approach	Test documents	Accuracy
		T	R	S			
[45]	Color	Y	Y	Y	Fuzzy integral of color clustering.	20 documents	Not mentioned
[49]	Color	Y	Y	Y	Color and contour skeleton analysis, shape fitting.	730 images	99.86%
[48]	Text	Y	N	N	Cross-correlation. Topology test by relative position and distance.	305 images with seal and 305 without seal	98.8%
[1]	Text	Y	Y	Y	GHT using labeled CCs.	Binary, 200 dpi	Not mentioned
[47]	Graphical information	Y	Y	Y	Outer boundary shape of seal, ellipse detection method.	Dataset1 (436), Dataset2 (193)	Not mentioned
[52]	Graphical information	Y	N	N	Run length smoothing, pixel density, CC.	4860	95.98%

eccentricity and rectangularity [59], geometric topology features extracted from components [61], area, isolation, deviation, symmetry, centralization, complexity and 2-level contour representation strings [71], global shape based features (circle, rectangle, triangle, ellipse, polygon, and B-spline) extracted from Fourier descriptor [62,72], shape context [73,3], features extracted from raw image/vector data [74], curvature [22], template matching [75], etc.

6.1.2. Classifiers used for logo recognition

Different classification methods employed for logo (well segmented) recognition/ classification can be categorized into non-parametric and parametric classification techniques. Non-parametric classifiers include: Nearest neighbor classification and matching based on similarity measures (Euclidean, Hausdorff distances, Cyclic Dynamic Time Warping) [54,66,5,6,55,11,59,65,57,61,2,71,70,73,72,63,12,3], indexing [56,60,74], hashing [58], template matching [75], etc. Parametric classifiers are: neural network [67–69], Naive Bayes classifier [62], AdaBoost learning approach [64], and normalized cross-covariance matching [22].

6.1.3. Logo recognition results and discussion

The results obtained from the pieces of work in the literature of logo and trademark recognition are provided in Table 5. From Table 5, it may be noted that most of the results have been reported on the University of Maryland Logo Dataset (UMLD) [54]. Both nearest neighbor and learning based classification approaches have frequently been used in the literature for the recognition of logos. However, the nearest neighbor based approaches are computationally expensive in the cases of high dimension features and a large number of instances. Hashing and indexing can be integrated in such a scenario to take care of high dimensionality and scalability. Learning based methods for the recognition are not also efficient when the number of classes is greater than 1000. In such a case, similarity based approaches seem to be more appropriate solution for the recognition purpose.

Based on the techniques reviewed for logo recognition, it may be noted that some systems used combination of two or more models for characterization of logos. Modeling structural and spatial information extracted based on line segments and computing dissimilarity between two sets of line segments provided a system invariant to scale, orientation, broken curves, noise and occlusion [55].

With reference to the features proposed for logo recognition in the literature, it may be noted that they are well adapted with the problem and they cover most of the issues (scale, rotation, translation, and occlusion), which may arise in logo recognition. The uses of semantic information (context + syntax + metric = semantics) by associating textual information (OCR) with the graphics [5,74,22] and feedback strategies [6] have improved the recognition/retrieval efficiency [5,6,74,22]. However, almost all the results reported for logo recognition have been obtained on a considerably small size dataset with a few classes of logos. Merit of the features and the classifiers on this small dataset (UMLD) cannot guarantee the same performance on large-scale data [60,2,71,3,58]. For example, we can see from Table 5 that some methods [66,67] obtained 99% accuracy when dataset is very small, whereas, some methods obtained less than 65% accuracy when large datasets have been considered [60]. Choosing of features and classifiers should be revised for such large-scale data with many classes of logos and also some indexing/hashing techniques need to be considered for the purpose. Regarding global and local features, it is known that recognition based on global features is sensitive to occlusion and over/under segmentation, since any missing part or redundant addition to a logo/seal can make the global features dramatically different. Local features, on the other hand, are less affected, but they mainly rely on the quality of document.

Specifically speaking, SIFT descriptors are segmentation free, robust to image tilt and perspective transformations [56], but high dimensionality of feature set and point matching in such a high dimension can be an issue when using SIFT descriptors. Features extracted based on transformation functions such as Wavelet and Gabor transforms as global

Table 5 – Comparative analysis of logo recognition results.

Method	Feature	Invariant to image transformation	Classifier	Dataset	Train	Test	Accuracy
[66]	Higher-order spectra	Y	Nearest neighbor	UMLD (105 logo classes)	3150 = 105 * 30 105 = 105 * 1	3150 = 105 * 30 3150 = 105 * 30	99.6% >90%
[67]	Gradient	N	Neural network	UMLD (40 logo classes)	4000 = 40 * 100	4000 = 40 * 100	99.15%
[68,69]	Gradient	N	Neural network	134 images, UMLD (105 logos) + 29	26800 = 200 * 134	26800 = 200 * 134	99.04
[5]	Text, primitive shapes (line, circle, triangle), global invariant (line, circle) and signatures features	Y	Indexing, matching	UMLD (100 logo classes)	NA	NA	NA
[55]	primitive shape (lines)	Y	Modified Hausdorff distance	189 images, UMLD (constructed using 20 logos) + hockey database	89	100	99%
[59]	Moments, structural features	Y	Nearest neighbor	UMLD	130	>130	NA
[60]	Local descriptors (SURF)	Y	Indexing	Flickr logo collection	4397	270	50%
[2]	Zernike moments	Y	Nearest neighbor	Korean and world trademarks	3000	3000	65% P
[71]	Area, isolation, deviation, symmetry, centralization, complexity, 2-level contour	Y for all except rotation	Fuzzy c-mean clustering		1000	50	P: 50% R: 76% Original, 88% 1st iteration, 94% 2nd iteration
[3]	representation strings	Y	Nearest neighbor	Tobacco800	432 (35 classes)	432 (35 classes)	87.08%
[58]	Shape context descriptors Local descriptors (SIFT)	Y	Hashing method	10,000 images of BelgaLogos dataset	NA	26 classes	25.7%

features are able to capture the variations in pixel intensity as well as the spatial separation of vertical, horizontal and diagonal edges in an image [70]. Furthermore, they have the advantages of multiple resolutions and ability to be reconstructed, however, in the cases of transformation variant wavelet may not work well for the recognition. Combination of angular spans of grids obtained from a gray level logo and Fourier coefficients of all segments provides a scale, rotation and translation invariant feature set for logo recognition [63], whereas, Fourier transformation is a well suited feature extraction for color/gray images (not for binary images). Moments based features are generally invariant under translation, scale, rotation, reflection and well suited when the logos are fairly segmented, but they are computationally expensive [79]. It is worth noting that all abovementioned features for logo recognition except SIFT [56], template matching [75] and combination of structural and spatial information [55] techniques cannot perform well when the logos are not accurately localized/detected in document images.

6.2. Related methods for seal recognition

In recognition methodologies, it is usually assumed that the seals are detected and localized. The same pipeline used for logo recognition is employed for seal recognition in the literature. Similar to logo, an unidentified seal is compared with every model of seals stored in a database following some matching criteria to recognize/verify the test seals. Often, before the verification process of the seal images with the registered images, an identification process has been performed to associate the input seal with a collection of possible registered seal images. Some of these identification and verification approaches are discussed as follows.

6.2.1. Seal identification

For seal identification purpose, Delaunay tessellation technique has been applied in [26]. The Delaunay graph structure is invariant to translation and rotation transformation, and it requires only local mesh restructuring. A Nearest Neighbor classifier using squared differences between the distributions of the triangular areas of model has been employed for the classification. Attributed stroke graph obtained from skeleton has been used for registration and identification of seal in [30]. Matching has been performed based on the skeleton image, and hence it is weak against local variety.

Some identification techniques use pixel-based shape descriptor considering the seal as a whole object. An ideal impression model has been created from an input seal impression [28]. The query seal image yet to be identified is rotated with an arbitrary angle. To do so, extracted character/graphical strokes from the query seal image need to be matched with the model reference images [28,30]. A matching seal pair must contain the same invariant structure in scale and rotation space. Since a seal imprint may be rotated, displaced, smeared due to improper pressing, or contaminated by ink blobs; handling such an invariant structure of seal is a difficult task.

In [76], a segmentation-based technique has been proposed using correlation coefficients obtained from transforming the round seal into a rectangular one. A feature of $4 * 4$

grid and an Eigen vector (from 8 feature of position code) have been used to decide for similarity matching and classified by different sequence of position codes. In [34], seal identification has been done using relative relation among segments of seal impression where features are extracted by fluency function approximation and performed relaxation matching. To do that, a set of breakpoints has initially been obtained from the contour of the seal. Next, the boundaries between a pair of adjacent breakpoints have been approximated with equi-paced knots quadratic fluency function. The fluency of curve has been determined by the least square rule. By approximating each interval between adjacent breakpoint of boundaries, the seal image is represented as an aggregate of segments. In [34], the authors have proposed the method handling blurred impressions, but it is effective only on some specific conditions.

In some research works, registration methods have been applied before verification task [77,49]. During seal imprint verification; correspondences of two samples (the reference and the test seal imprints) are rotated so that they are aligned before verification. In [77], a method based on contour analysis has been proposed to find principal orientation of a seal where it has been assumed that contour chain with longer length represents more significant information. Input seal has initially been converted into a binary image and the comparison of extracted moment based features has been performed for seal registration. In [49], first Fast Fourier Transformation (FFT) has been performed and then a 3-level coarse to fine approach using wedge-ring-detector (2 rings and 16 wedges) method has been employed for seal registration. A point matching score has been computed between superposition of two seals to obtain a match score. Experiment on 10 seals of different shapes (e.g. rectangle, circle and ellipse) shows 82% and 74.9% average point matching score.

6.2.2. Seal verification

The seal verification has been performed comparing the input seal impression on the paper with the reference seal impression on the paper, which has been registered beforehand [28]. In [33], a seal imprint verification system has been presented integrating different local and global features such as strokes outer points, line width of strokes, mean radius, and average line width in conjunction with a dissimilarity measure. Seal verification has also been performed in literature using correlation algorithm [28,29,19]. In [28], a range-finder has been used to detect the rough seal surface with 3D data slant. Rotation, position, slant and pressure have been corrected using a parameter-searching algorithm. In [29], a “correlation-based algorithm” has been proposed for seal imprint verification. This algorithm is able to verify seal imprints in a robust manner with regard to quality variation, but it may not have enough ability of detecting forgery with a very similar pattern to that of a genuine one. A heuristic based method using correlation cost function has been used to find the best congruent transformation between a model and a sample seal imprint [19]. It was concluded that cause of miss-verification was nothing but the various impression qualities by affixing conditions [19].

A verification method based on stroke edge matching with the use of a pixel-based shape descriptor has been presented

in [27]. Seal has been considered as a whole object for the analysis and verification [27]. In [31], seal verification has been performed using the discrete K–L expansion of the discrete cosine transform (DCT). Mainly, DCT coefficients extracted from autocorrelation of Wiener filter output sequence have been considered to represent the feature of the seal imprint [31]. The Wiener filter has been used to reduce the quantization error of computing the Zernike moments for the rotated seal imprint contaminated with noise. Rotation invariant features by the coefficients of 2D Fourier series expansion of the log-polar image have been presented [32]. Seal imprint has been verified by the Eigen vector corresponding to the largest Eigen value of a matrix defined in terms of the above Fourier coefficients [32]. Correlation-based block matching in polar coordinate system has been proposed in [13] for seal verification. Rotation-invariance features have been computed based on center information of CCs converted into polar co-ordinate plane.

6.2.3. Seal verification/recognition results and discussion

The techniques used for seal recognition in document images are briefly outlined in Table 6. From Table 6, we note that seal involves rich textual structure with a bigger boundary frame and text components. Because of its rigid nature, often correlation-based approaches [28,29,19,33] have been used in the literature for the verification. Hard-matching approaches performed by template matching may not work when a seal contains variable field. Seal text components and their relative information [1] can be used efficiently to take care of multi-scale, multi-oriented text with different fonts. Pixel-based shape descriptor and stroke edge information [27] can also provide good performance in translation, rotation and scale invariant seal matching. Structural information [26, 19,30] of seal components can be an appropriate choice to be used for seal recognition.

7. Benchmarks and available datasets

Considering the literature of logo and seal detection/recognition, a few datasets are publicly available for the research purposes [54,60,58,43,32,50]. To the best of our knowledge the only dataset, which includes real documents that can be used for logo/seal detection is Tobacco-800 dataset [43]. This dataset is freely available for the research purposes. The Tobacco-800 dataset contains 1290 document images of which 412 documents contain 432 logos. The logos are mainly graphical logos. The resolutions of documents in the Tobacco-800 vary from 150 to 300 dpi and the size of images ranges from $1200 * 1600$ to $2500 * 3200$ pixels. The ground truths for logos and seals in this large complex document image collection have also been provided. The ground truth includes the location and dimensions of each visual entity, enabling evaluation of logo detection and signature matching [43]. Most of the reported results in the literature for logo and seal detection are based on the Tobacco-800 dataset.

For logo recognition and trademark retrieval/recognition, the University of Maryland Logo Dataset (UMLD) [54], Flickr logo collection [60], and BelgaLogos Dataset [58,50] have mostly been used in the literature. In the literature of logo

recognition methods, most of the experiments have been performed on the UMLD. The UMLD contains 106 logo images in 8 bit gray scale [54]. For logo and trademark retrieval/recognition, Flickr logo collection [60], and BelgaLogos Dataset [58] have been considered for the experimentations. Flickr logo collection [60] is a collection of vintage logos from a mid-70s edition of the book “World of Logotypes”.

BelgaLogos dataset as a collection of large natural images has specifically been created for the content-based logos and trademarks retrieval. The dataset is freely available for research purpose. The BelgaLogos dataset is composed of 10,000 images of different companies, such as finance and social affairs, sports, culture, politics, economics, and personalities. The images are in JPEG format and each image has two different ground truths: a global and a local ground truth. For the global ground truth, each image is labeled for each logo (26 different logos) with 1 if the logo is actually present in the image and with 0 if it is not. In the local ground truth, for every logo a rectangular bounding box has been considered. A given image can contain several bounding boxes. The annotated instances have then been classified as “OK” or “Junk” manually by 3 persons, based on their ability to easily recognize a logo without the image context [58,50].

Apart from these datasets some other datasets mentioned in Tables 3–6 have also been used for logo/seal detection/recognition/retrieval [16]. However, they have not been delivered publicly for the research use.

8. Discussion and remarks

From the related literature on logo and seal recognition/identification/retrieval, it can be concluded that recognition/retrieval methods for logo and seal on small size datasets with limited number of classes (models) are a well-documented problem and can be considered as a solved problem. However, it is not the case when the number of classes is large as shown in the literature (Tables 5 and 6). When the number of classes and consecutively the size of data are increasing, the use of some hashing/indexing techniques [78] in addition to the choosing suitable features and classifiers with respect to the size of data and application is desirable. Moreover, there are various shortcomings in the existing methods with respect to the feature extraction, classification and suitability of the methods that need to be carefully considered in order to choose an appropriate solution for a particular problem. Some of the drawbacks are outlined in the following.

Regarding feature extraction methods for logo/seal recognition/retrieval, the following points can be stated: (i) a major problem with the use of global features, such as Moments [59,71,31] and negative shape [59], is their weakness to noise, occlusion and over/under segmentation problems, which significantly change the shape of logos and seals, (ii) the features based on connected components and primitives (lines, curves and circles) are sensitive to degradation, broken and touching components [1,27,47], (iii) the features should be generic to be able to deal with both graphical and textual information, since, the features devoted to graphical/text recognition may not work on textual/graphical samples [2,30], and

Table 6 – Comparative analysis of seal verification/recognition results.

Method	Feature	Invariant to image transformation			Classifier	Dataset	Accuracy
		T	R	S			
[26]	Distribution of triangular area from Delaunay tessellation	Y	Y	N	Nearest neighbor	30 Gray images (256 × 256)	Not mentioned
[27]	Pixel-based shape descriptor and stroke edge matching	Y	Y	Y	Similarity measure	8 imprints (250 × 250), 160 tests	1.87% incorrect
[28]	Correlation-based algorithm in 3d space	Y	Y	NA	Multi-resolution mount-climbing search	5 different seals, 50 images	98% (min similarity threshold) and 94% (max similarity threshold)
[29]	Correlation-based algorithm for verification	Y	Y	NA	Correlation cost function	5 genuine and 5 forged seals, total 1000 images	99.8%
[19]	Structural and correlation feature	Y	Y	NA	K–L approach and feature difference	2500 images	>98%
[30]	Attributed stroke graph obtained from skeleton	Y	Y	Y	Distance measure according to minimum square error transform	3 models and 24 test imprints of each, 72 test data	90.3%
[32]	Coefficients of 2D Fourier of log-polar image	Y	Y	Y	Distance based on inner product	1020 seal images of 34 classes	99.67%
[31]	Zernike moment, Wiener filter, discrete cosine transform (DCT)	Y	Y	N	Discrete K–L expansion of DCT	70 seal images of 3 classes	100%
[33]	Multi-expert system using color, feature and correlation based algorithms	Y	NA	NA	Voting approach	5 models, 500 genuine + 750 forged seal imprints	FAR = 0.4% FRR = 1.1% Rejection rate 12.3%
[34]	Fluency function approximation	N	N	N	Relaxation matching	256 × 256, Binary image. 4 models, 80 imprints	88.8%
[1]	Generalized Hough Transform (GHT) using connected components	Y	Y	Y	Voting approach	220 Binary images, 5 Fold Cross Validation	92.42%

(iv) SURF and SIFT features based on intensity/color information mostly work on gray and color images, in the case of binary images these features may not be suitable for logo/seal recognition [24,15,16].

Considering the classification methods used for logo and seal recognition/retrieval, it is evident that (i) neural networks [67–69] generally require considerable number of samples for training, so this kind of approach is not suitable when a limited number of instances are available for training [62, 23], and (ii) nearest neighbor [59,2,3,26,27,32], Modified Hausdorff distance [55] and matching based methods [5,60,34] are generally of high time complexity, as these methods need to deal with a high dimension feature space and a large number of instances for training.

On suitability of the techniques, particularly, dedicated to the recognition of logos/seals respecting complexity and strategy itself, the following issues are the main concern: (i) a major problem with the approaches using structural analysis is that they are not robust to noise/occlusion, which change the structure of logos/seals, (ii) the performance of

the wavelet-based method decreases rapidly with increasing swirl [6], (iii) the bipartite graph matching approach is not suitable for a big size data, as the bipartite graph is a problem with $O(N^3)$ time complexity, (iv) most symbol recognition methods work with a known database of reference symbols, or with a learning phase, it is, however, impossible to precompile all possible symbols, or to perform a time expensive learning procedure in some applications [12], and (v) the approach based on OCR results for logo and seal recognition [22,1] may not perform well, as seals/logos may be in any orientation/skew in document images and recognition of such multi oriented characters in logo/seal document images is not an easy task.

9. Conclusion and future directions

In spite of considerable amount of work afforded for logo and seal detection/spotting in the literature, this problem still

needs more efforts and research. Since detection/spotting result has direct effect to the recognition/retrieval accuracy, it is reasonable to have a feedback from the recognition/retrieval step to the detection/spotting step allowing the detection step to correct itself. Therefore, developing strategies, which consider both the problems of detection/spotting and recognition/retrieval in a single framework using some feedback policies, can improve the overall system performance. In such a scenario, the recognition task must be accomplished quickly in the presence of geometric transformation, noise, over/under segmentation and possible occlusion [5,75].

Furthermore, for choosing a suitable methodology for an efficient logo/seal detection/spotting followed by recognition/retrieval the following facts can be considered: (i) techniques based on connected component analysis are time consuming and sensitive to noise, skew and degradation, (ii) techniques which focus on text and graphic separation cannot deal fairly with textual logos and seals [39], (iii) technique based on CC analysis and text/graphic separation cannot perform well when the data in training and testing are incoherent and inconsistent, (iv) the assumption that components of a logo/seal are near to each other and they can be grouped together by scaling the image or finding their neighborhoods is also too restrictive, as the clutter image background or the large variance of logos/seals designs [38], (v) the techniques based on window-sliding may be called as zone classification rather than logo extraction [17], (vi) the techniques based on local detectors are not still well adapted to the problem of logo and seal detection/spotting in binary document images, as they are dedicated to gray/color scene images where intensity variability plays an important role in the detector accuracy [24,15,16,40], (vii) computation and matching of local descriptors is of polynomial time complexity and this complexity may burden logo/seal detection in document images [24,52] where features space is of high dimension and the number of reference logos/seals and document images is quite large, and (viii) bag-of-words model cannot preserve the spatial arrangement of features and in case of needing invariant features for logo/seal detection/recognition, this technique may not work efficiently [6].

To conclude, the above points can be considered by researchers to deliberately provide their efforts for proposing more efficient systems in this research domain. The authors also think the remarks and suggestions provided in this survey will be useful to readers in choosing a suitable strategy, feature, classification, etc. for developing logo/seal based administrative document image analysis applications.

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