Document seal detection using GHT and character proximity graphs

Partha Pratim Roy [a,*], Umapada Pal [b], Josep Lladós [a]

[a] Computer Vision Centre, Universitat Autonoma de Barcelona, Spain
[b] CVPR Unit, Indian Statistical Institute, Kolkata, India

ABSTRACT

This paper deals with automatic detection of seal (stamp) from documents with cluttered background. Seal detection involves a difficult challenge due to its multi-oriented nature, arbitrary shape, overlapping of its part with signature, noise, etc. Here, a seal object is characterized by scale and rotation invariant spatial feature descriptors computed from recognition result of individual connected components (characters). Scale and rotation invariant features are used in a Support Vector Machine (SVM) classifier to recognize multi-scale and multi-oriented text characters. The concept of generalized Hough transform (GHT) is used to detect the seal and a voting scheme is designed for finding possible location of the seal in a document based on the spatial feature descriptor of neighboring component pairs. The peak of votes in GHT accumulator validates the hypothesis to locate the seal in a document. Experiment is performed in an archive of historical documents of handwritten/printed English text. Experimental results show that the method is robust in locating seal instances of arbitrary shape and orientation in documents, and also efficient in indexing a collection of documents for retrieval purposes.

1. Introduction

In the last few years, intensive research has been performed on content-based image retrieval (CBIR) and consequently a wide range of techniques have been proposed [8]. CBIR consists of retrieving visually similar images from an image database based on a given query image. Digitized document is a particular case of image. Libraries and archives are generally interested in mass-digitization and transcription of their book collections. The objective is not only preservation in a digital format of documents of high value, but also to provide access and retrieval services to wider users, and assist scholarly research activities. On the other hand, companies are interested in implementing digital mailrooms to improve the efficiency of paper-intensive workflows and to reduce the burden of information processing of incoming mails, faxes, forms, invoices, reports, employee records, etc. By this digital mailroom, companies try an automatic distribution of incoming mails to their respective departments based on the content of electronic documents. Content-based document image retrieval (CBDIR) is a subdivision of CBIR where large scale document retrieval is performed according to users requests.

Documents are containers of information made by humans to be read by humans. CBDIR involves a search process where the user's request is a concept to be found. Traditionally, document retrieval is associated to textual queries. The records in typewritten and structured documents are indexed with the traditional high performing commercial Optical Character Recognition (OCR) products. Once the image document is OCRed, the resulting ascii information is compared with the query with a string search algorithm. The OCR techniques may fail in documents with high degree of degradation such as faxes due to compression or bilevel conversion, historical documents databases which are often degraded due to aging or poor typing, or handwritten documents. For such type of documents, word-spotting [22,28] provides an alternative approach for index generation. Word spotting is a content-based retrieval process that produces a ranked list of word images that are similar to a query word image. The matching for word spotting is done at image level through word shape coding. To obtain shape code of a word, different zonal information of the word can be used.

1.1. Motivation

Besides huge amount of text strings, some documents contain a large amount of information that is usually neglected and can provide richer knowledge. There are documents comprising mostly graphical information, like maps, engineering drawings, diagrams and musical scores. Old documents contain decorative initials and separators. Administrative documents contain graphical symbols such as logos, stamps or seals. Searching in terms of symbol queries such as logos or seals allow the quick filtering or routing of the document to the right business process, archive or individual. Thus the detection of these graphical symbols in documents increases the performance of document retrieval [35,37]. Given a single instance of

* Corresponding author.
  E-mail address: 2partharoy@gmail.com (P.P. Roy).

a symbol queried by the user, the system has to return a ranked list of segmented locations where the queried symbol is probable to be found. Traditional word-spotting methods which are devised to extract row/column-wise features from segmented image may not be useful for such purpose. Following the idea of word spotting, the problem of locating a graphical symbol in a document image is called *symbol spotting*. If we extend the idea of symbol spotting to a database of document images, i.e. a digital library, the problem is called *symbol focused retrieval* [32]. The arrangement of featured key-points are used to retrieve document images [25]. These methods are promising in detecting objects in general in terms of accuracy, time and scalability. Graphical objects such as symbols, seals, logos, etc. are synthetic entities consisting of uniform regions and these are highly structured [32,33]. These facts make geometric relationships between primitives and discriminative cue to spot symbols.

Indexing of documents can be performed based on graphical entities. In this paper we propose a scheme on document indexing based on seal information. Seals are complex entities consisting of mixed textual and graphical components. Information obtained from seals could be used for efficient storage and retrieval of the documents. Seals generally have closed, connective contour surrounding text characters, and logos which indicate owner and usage of the seal [19]. They bear some constant character strings to convey the information about the owner-organization and its locality. Besides, in many instances seal contains some variable fields such as date [26]. Date may provide the sending or receiving information of the document. Hence, automatic seal detection and recognition is an important stage to follow this task. It also allows to identify the document sources reliably.

Detection and recognition of seals are challenging tasks because seals are generally unstable and sometimes contain unpredictable patterns due to imperfect ink condition, uneven surface contact, noise, etc. [38]. Overlapping of seals with text/signatures, missing part of a seal, etc. are typical problems and add difficulty in seal detection. A seal instance may be affixed on any position within the document, which requires detection to be carried out on the entire document. Also a seal may be placed in arbitrary orientation. See Fig. 1(a), where a historical archive document containing a seal is shown. The seal is overlapped here with part of signature and text regions. As a result some information of the seal is missing/illegible. We also show a postal document in Fig. 1(b) which contains a seal overlapped with stamp images. It is to be noticed that, due to overlapping and noise, many text characters of the seal are missing.

1.2. Related work

Detection of seals in documents can be treated as localizing objects in different pose. In many instances seals and text are in different colors, and to handle such document some researchers have studied the detection process based on color analysis [10,35]. In mass digitization process due to compression or bi-level conversion, color analysis can only solve a set of problems. A prior knowledge of the outer boundary shape of seal (e.g. circular, rectangular, elliptical, etc.) is helpful to locate seal in documents [38]. A further seal recognition technique is needed here because, it is difficult to recognize the seal if text information within seal is different although the boundary shape is similar. Thus many times seal has been treated as a symbol and methodology like segmentation by Delaunay tessellation [7] are applied for seal recognition. Hu et al. [15] proposed a heuristic method to find the best congruent transformation between the model and sample seal imprint. Correlation-based algorithm for seal imprint verification is also presented in [12,13]. Chen [5] used correlation-based block matching in polar coordinate system based on rotation-invariance features. Since, under the constraint of fixed scanning resolution, seal information can be trained in priori.

Multi-scale is not necessary for seal detection in documents. But multi-rotation features are needed. He also proposed a method using contour analysis to find the principal orientation of seal [6]. Matsuura et al. [23] verified seal image by using the discrete K–L expansion of the discrete cosine transform (DCT). Rotation invariant features by the coefficients of 2D Fourier series expansion of the log-polar image is presented in [24]. Lee and Kim [18] used the attributed stroke graph, obtained from skeleton, for registration and classification of seal. Gao et al. [11] used a verification method based on stroke edge matching. These techniques [11,18] use pixel-based shape descriptor considering the seal as a whole object. Seal involves rich textual structure with a bigger boundary frame and smaller text components. In Fig. 2(a), we show two different seal images containing similar circular boundary frames but different text information. They contain a set of text characters along with a symbol. Text strings are designed in different font, orientations and sizes. In Fig. 2(b) we show a class of oval-shaped seal having noise (missing seal information or presence of other text characters from document). Because of different orientation, font, sizes, etc. boundary information [38] or pixel-based methods [11,18] are not sufficient to discriminate the seals properly. Moreover, to take care of multi-oriented seal, pixel-based method needs higher computational time.
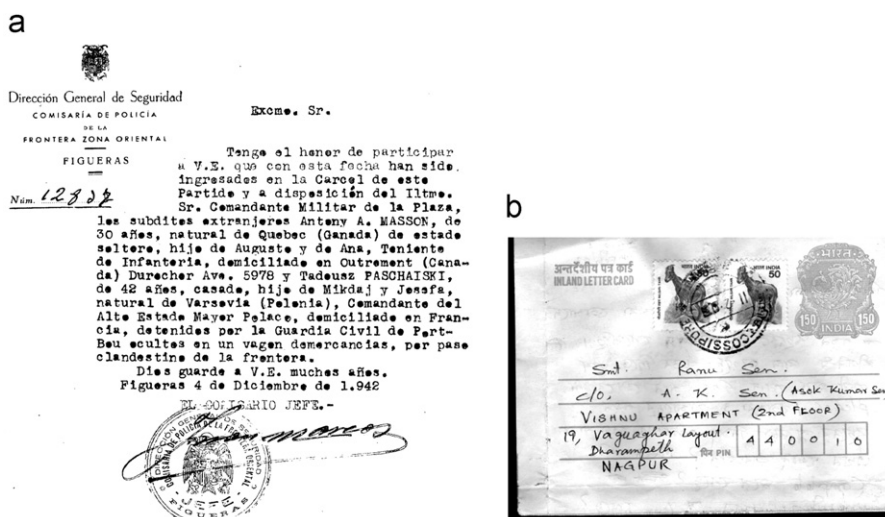

Fig. 1. (a) A historical document with a seal. The seal is overlapped with the signature here and (b) A post-card image showing a seal with cluttered background.
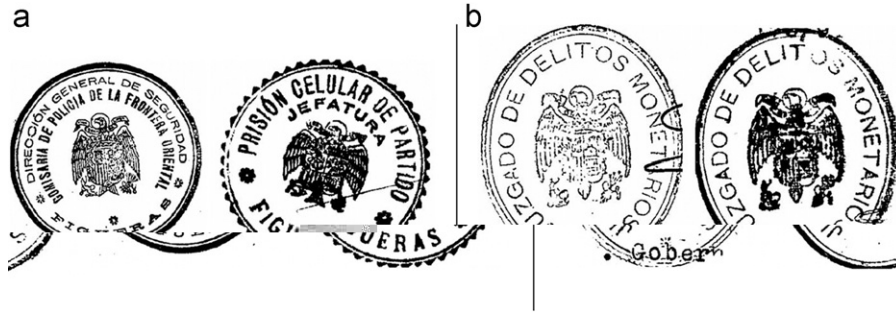
Fig. 2. (a) Seals containing similar circular frames but different text information and (b) Different noise level in a single class of oval-shaped seals.

Also, hard-matching approach [5] performed by template matching may not work when a seal contains variable field such as date. Text information is important part of seal and we needed a higher level of feature using text information rather than just pixels to handle recognition of seals.

1.3. Generalized Hough transform

Generalized Hough transform (*GHT*) [2] is the extension of the idea of the "standard" Hough transform (*HT*), which is a feature extraction technique originally devised to detect analytical curves (e.g. line, circle, etc.). The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure. The modification of *GHT* enables this technique to be used to detect arbitrary objects (non-analytical curves) described with its model.

A look-up-table called R-table is used in GHT to store information concerning the template of the object to be detected. Given an object, the centroid is chosen usually as reference point (x_c, y_c) [3]. From this reference point, data from each point on the object's edge is recorded in R-table. Let, the line joining from a boundary point (x, y) to the reference point makes an angle (α) with the *x*-axis. Also, '*r*' be the distance from that boundary point to the reference point as shown in Fig. 3. R-table is constructed to store (α, r) of each boundary point by indexing with its gradient angle (ϕ) as shown in Table 1. From the pair (α, r), the reference point can be reconstructed.

Given a test image, an accumulator (A) is defined in the parameter space. The accumulator records the votes of the edge points to determine the most probable center of the prototype object. More specifically, the gradient angle ϕ_i which is obtained from each edge point (u_i, v_i) of the test image is utilized to retrieve corresponding entries of the R-table. The possible location of reference point in the parameter space is calculated by the following equation:

$$(x_{ci}, y_{ci}) = u_i + r(\phi_i)\cos[\alpha(\phi_i)], v_i + r(\phi_i)\sin[\alpha(\phi_i)] \qquad (1)$$

In this equation, (x_{ci}, y_{ci}) denotes the location of the possible reference point. And, $r(\phi_i)$ and $\alpha(\phi_i)$ signify the magnitude and the angle of the position vector obtained from the R-table for index ϕ_i, respectively.

A classical pixel-based GHT may not be efficient for seal detection because two different seals having similar frame boundary (such as circular, rectangular, etc.) cannot be distinguished properly. Seals generally comprised of many text characters. In our approach, text characters in a seal are considered as high level descriptors and these text characters are used to cast vote for detecting seals. We use character pair information, inter-character distance and angle information to describe the spatial information. Since, the spatial information among text characters will remain fixed, the relative position of them is used to vote for seal detection.
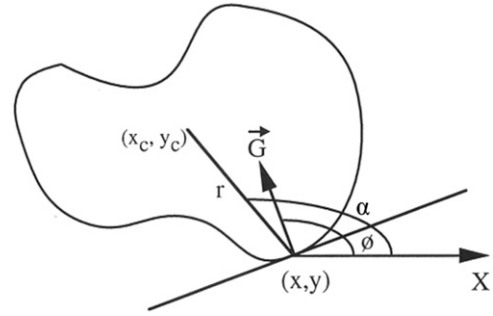

Fig. 3. The geometry used to construct the R-table in GHT.

Table 1
The R-Table constructed for Fig. 3.

Gradient angle	(α, r) pairs
ϕ_1	$(\alpha^1, r^1)_1, (\alpha^2, r^2)_1, \ldots (\alpha^n, r^n)_1$
ϕ_2	$(\alpha^1, r^1)_2, (\alpha^2, r^2)_2, \ldots (\alpha^n, r^n)_2$
.	.
.	.
ϕ_m	$(\alpha^1, r^1)_m, (\alpha^2, r^2)_m, \ldots (\alpha^n, r^n)_m$

1.4. Outline of the approach

In this paper we propose a scheme on document indexing based on seal detection and text information has been used for this purpose. When imprinted, seal produces a fixed set of text characters with a logo (sometimes) to describe its identity. Although the boundary frames are similar in some seals, they may contain different text information. We classify them as different types of seals. So, it is important to take care of text information knowledge in seal recognition purpose. Text characters in seal are of multi-rotations and multi-scale. The font styles vary according to the design by its owner/organization. Generally seals are affixed in documents that also contain a huge amount of text characters. Thus, text information within seal may be degraded due to the overlapping with text present in that document. In seal, the relative positions among neighboring text characters are fixed. This is a key observation in our formulation. In literature, we find, distance between connected components was exploited as a basic feature in Docstrum [27]. The Docstrum is the plot of distance and angle of all nearest-neighbor pairs of a document image. Distance and angle are computed from k-nearest neighbor pairs of connected components. The plotting information is used to analyze higher level layout structure like line extraction, skew estimation, etc. of the document. In our approach, features computed from spatial information of text characters along with their corresponding text labels obtained after recognition are used to detect the seal efficiently.

Our proposal of seal detection approach is based on the concept of GHT. Instead of feature points, the text characters in the seal are used as basic features for seal detection. We label the local connected components of a seal as alpha-numeric text characters. To obtain this, we employ multi-scale and multi-oriented text character recognition using a Support Vector Machine (SVM) classifier. The recognized text characters are used to provide high level descriptor in our approach. For each component (text character) we find its n-nearest neighbors. Next for each pair of components, we encode their relative spatial information using their distance and angular position. Given a query seal we compute the relative spatial organization for pair-wise text components within seal. These information are stored into a spatial feature bank. In an image, for each neighboring component pair, we use this spatial feature bank to retrieve query seal hypothesis. A vote is casted for possible location of the seal based on the matching of neighboring component pairs to ensure detection of partial seal objects. The locus of a high number of votes (the peak) are the result of the seal spotting. Votes in GHT accumulator validates the hypothesis to locate the seal.

The main contribution of this paper is to use of recognized local text components as high level descriptors and to generate hypothesis of the seal location based on spatial arrangement of these descriptors. Our approach is based on local text characters instead of only pixel-level descriptors to overcome distortion and affine-transform problems which are main drawbacks in existing approaches. Also, we have formulated our approach to be scalable and adaptive to process large collection of documents. It does not need a previous segmentation, thus provides direct focus on seal detection. The approach is robust to detect seal in noisy, cluttered document. We can therefore conclude that combining individual character recognition with a SVM and relational indexing using GHT method, our work can be classified as a combination of statistical and structural approach.

The rest of the paper is organized as follows. In Section 2, we explain the local component extraction and recognition procedure in brief. In Section 3, we describe the representation of the seal and its detection process. The experimental results are presented in Section 4. Finally conclusion is given in Section 5.

2. Text character extraction and identification

Labeling of individual characters in multi-oriented and multi-sized environment drives the detection of seal objects in documents in our approach. In a seal, apart from text, there may exist non-text components due to presence of form/table in the document or strokes from signatures which may touch/overlap the text characters in the seal (see Fig. 1). For extraction of text components, we assume the size of text components is smaller compared to that of non-text components (graphical components). Based on the area and aspect ratio of connected components, isolated text characters are extracted using area-histogram analysis [34].

Recognition of text characters in multi-rotation and multi-scale environment is a challenging task. Chain code histogram (CCH)

technique [16] based on contour of shape is sensitive to small rotation. There exist some shape descriptors like Hu's moments [14], Zernike moments [17], angular radial transform (ART) [29], Fourier–Mellin [1], angle-based features [30] etc., which are invariant to rotation, translation and scale. Angle-based features was proposed in our earlier paper [30] for text character recognition which have been found best among different shape descriptors. In our system, we have used angle-based feature for recognition purpose and it is briefly discussed as follows.

Our *angle-based feature* descriptor is a zone-wise feature descriptor to describe symbol/text characters. It is based on histogram of contour angle information in different zones. It may be noted that our feature differs from *shape context* [4] that uses histogram of distances between pair of pixels.

Circular ring and convex hull ring-based concept have been used to divide a character into several zones to compute features. To make the system rotation invariant, the features are mainly based on angular information of the external and internal contour pixels of the characters. Given a sequence of consecutive contour pixels $V_1 \ldots V_i \ldots V_n$ of length n, the angle of the pixel V_i is the angle formed at V_i by three pixels V_{i-k}, V_i and V_{i+k} (Here, $2 \times k$ is the total number of the neighbor pixels of V_i considered for angle computation, k pixels before V_i and k pixels after V_i). For a better angular information of a pixel V_i, we consider two angles obtained by considering $k = 3$ and 4, and the average of the two angles is the estimated value of the pixel V_i. The angles obtained from all the contour pixels of a character are grouped into 8 bins corresponding to eight angular intervals of $45°$ ($337.5°$ to $22.5°$ as bin no. 1, $22.5–67.5$ as bin no. 2, $67.5–112.5$ as bin no. 3, etc.). We compute total number of angles in each bin and this number is the frequency of the angular information of a bin. For a character, frequency of the angles of 8 bins will be similar even if the character is rotated at any angle in any direction. For illustration, see Fig. 4. Here, we compute the histogram of the angles corresponding to 8 bins of two rotated shapes of three characters 'W', 'G', 'T'. From the figure it can be noted that angle histogram of each pair of characters is similar although the characters have different rotations.

Circular and convex hull rings are constructed on a character as follows. A set of seven circular rings is considered here and they are defined as the concentric circles considering their centre as the centre of minimum enclosing circle (MEC) of the character and the minimum enclosing circle is considered as the outer ring. The radii of the rings are chosen such that, the area of each ring is equal. Similarly, convex hull rings are also constructed from the convex hull shape of the character. In a ring we get eight values (number of angles) for eight different angular bins. These values are used as features. For a character with seven circular or convex hull rings, we have 56 features (7 rings $\times$ 8 values in each ring). To get more local feature, slope feature is computed from tangent of contour pixel with respect to its angle of radius. This angle features from each bin are grouped into eight sets corresponding to eight angular information of $45°$ (as discussed above). Thus, for 8 bins of contour pixels, we have $8 \times 8 = 64$ dimensional slope features. As a result,
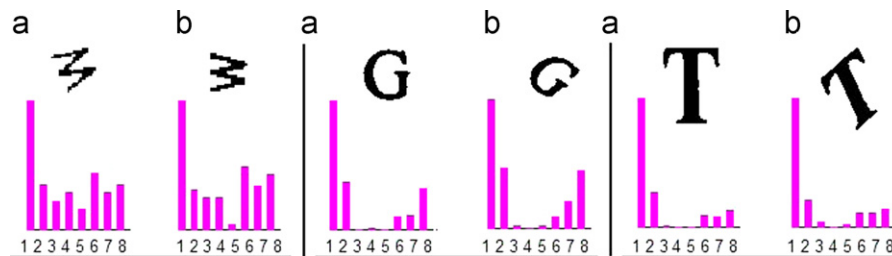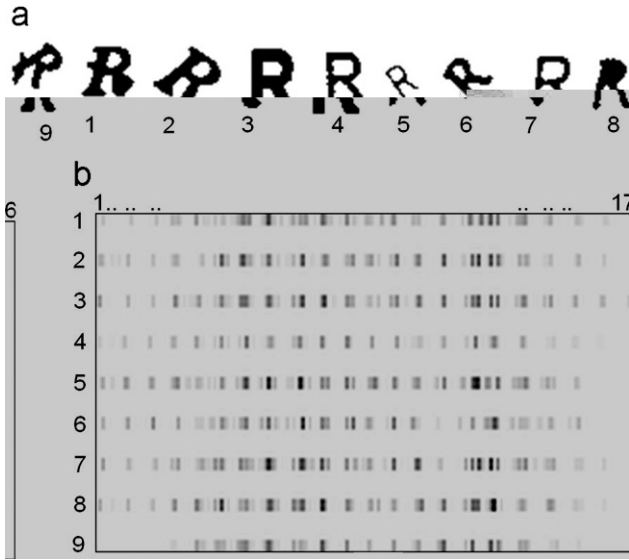

Fig. 4. Input images of the characters 'W', 'G', 'T' in two different rotations and their angle histogram of contour pixels are shown. The numbers 1–8 represent eight angular bins.

Table 2
List of similar shaped characters. Characters in a cell are treated as same class.

b q	P p d	7 L	0 O o	6 9	1 I l i	J j
S s	u n U	V v	N Z z	X x	W w M m	C c

Fig. 5. (a) Some samples of character 'R' from the dataset are shown and (b) Each element of 176-feature vector are displayed horizontally with its gray scale value for each sample of 'R'.

we have 176 [56 (for circular rings)+56 (for convex hull rings) +64(slope feature)] dimensional feature vector for the classification. The feature dimension has been selected based on experiment and to make the scale invariant, the feature vector is normalized dividing it by the total number of contour pixels. We feed these feature into a *SVM* classifier (Gaussian kernel with radial basis function) for recognition [36].

Both English uppercase and lowercase alpha-numeric characters were considered, so we should have 62 classes (26 for uppercase, 26 for lowercase and 10 for digit). But because of shape similarity due to orientation, some of the characters like 'd' and 'p'; 'b' and 'q'; etc. are grouped together. We show the equivalence classes in Table 2. Here, all the characters in a class are considered as equivalent because one character of a class can be obtained from other characters of the class by a rotation. Different fonts of characters have been trained for recognition purpose. To get an idea of quality of extracted text characters, we show some samples of character 'R' in Fig. 5(a). Gray value representation of the feature vector of the multi-oriented samples shown in Fig. 5(a) are displayed in Fig. 5(b). From the figure it can be seen that, although the characters are multi-oriented, the corresponding features are similar. Given a connected component image of a seal, we compute the recognition label (ascii value) to obtain the corresponding class and use this value for our seal detection method.

3. Seal detection using GHT

Seals in documents are affected mainly due to noise, rotation, occlusion and overlapping. To take care of these problems, our approach is based on partial matching which is inspired by *GHT* [2]. Here, we describe the architecture of our method with four key-parts namely: spatial information extraction, construction of R-table, seal recognition and detection approach. The former two

allow to represent model shapes in a compact way. The latter two are the steps when a query is formulated into the image database. Let us further describe the above steps in the following subsections.

3.1. Feature descriptor of a seal shape

Our representation model for a seal is based on the connected components (classified as text characters) within seal region. Due to natural spatial arrangement of text characters among them, we characterize the seal information based on relative position of the local text character shapes. The attributes used in our approach are described below.

1. *Reference point of a seal* (R_s): Given a seal image, the center of the minimum enclosing circle (MEC) of the seal is considered as the reference point (R_s). Note that, the relative position of R_s will be fixed for each class of seal shapes even if the seal is rotated.

2. *List of component pair*: To represent the spatial arrangement of the components present in the seal a list of neighboring component pairs is built. These neighboring component pairs are selected based on their proximity. Each component is associated to its *n*-nearest components. The neighbor components are decided using boundary growing algorithm from the boundary of the corresponding component. To find neighbor of a component, boundary of the component is grown until the grown boundary touches another component. The component to which it touches first is the first neighbor component. The component to which it touches next is the second neighbor component and so on.
   Formally, a proximity graph $G=(V,E)$ is created to store these neighboring component pairs (here V=vertices and E=edges). Let there be T_s components in a seal, thus, $\|V\| = T_s$. An edge, $e_{ij} \in E$ is formed by a component pair (C_i,C_j) if components C_i and C_j are neighbors. See Fig. 6(a), where the *n*-neighbor (*n*=5) components of 'U' (according to distance) are shown by joining line, which are 'L','L','F','A' and 'T'.
   From each neighboring component pair, the location of the reference point (R_s) of the seal is designated. The spatial information of each neighboring component pair with respect to R_s is done by simple basic features: distance and relative angle discussed as follows.

3. *Distance*: We compute the CG (center of gravity) of each component for this purpose. Let, G_i represents the CG of component C_i. In Fig. 6(b), the distance d_{ij} is shown for two components 'A' and 'D' of seal. To obtain scale invariance, the distance is normalized based on character pair sizes.

4. *Relative angle*: Two angles are considered for each neighboring component pair for detection purpose. For each pair of components we may consider a triangle by their G_i, G_j with R_s (see Fig. 6(b)). Angle α_i is formed at G_i by $G_j (j \neq i)$ and R_s. These angles are denoted by α_i and α_j. In Fig. 6(b), these angles are "$\angle R_s AD$", "$\angle ADR_s$", respectively.

Given a pair of neighboring connected components of a seal model (m), we compute the feature information for our approach. The ascii character labels of components are found by the recognition using SVM. Let L_i (L_j) denotes the ascii character label of a character component C_i (C_j). The distance and relative angles are calculated through their spatial organization. Thus, for each neighboring component pair C_i and C_j of the seal (m), the feature information f_{ij}^m is obtained as given below.

$$f_{ij}^m = (L_i, L_j, d_{ij}, \alpha_i, \alpha_j, m)$$

The feature of all neighboring character pairs characterizes the spatial description of seal. These features are stored in a R-table for indexing purpose.
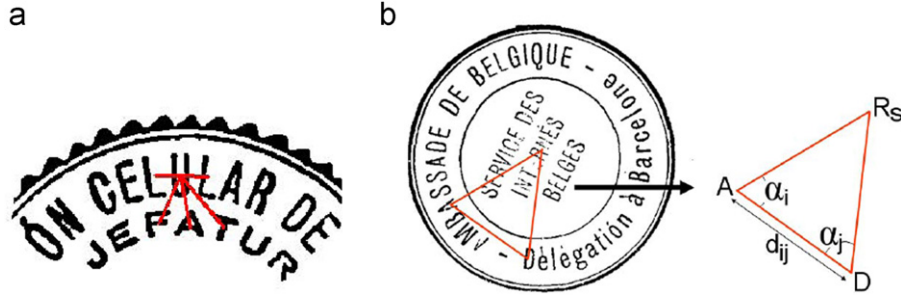
Fig. 6. (a) Character and its n-nearest neighbors are shown for the character 'U' and (b) A neighboring character pair and their relative angles are shown in a seal. Here, R_s is the reference point of the seal.
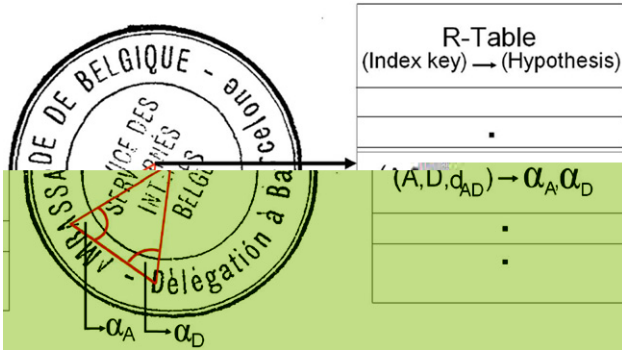

Fig. 7. R-table representation from a seal model. Here, the triplet (A, D, d_{AD}) represents the index key for the character pair 'A' and 'D'. (α_A, α_D) are stored as hypothesis of the corresponding triplet of the index key.

Fig. 8. Efficient architecture of R-table and relation to feature information.

3.2. Construction of R-table

The feature information of each neighboring character pair of a seal is computed and stored in a hash table called as R-table of GHT using an efficient way. The construction of R-table is performed as follows. We encode the character label and distance information for each neighboring character pair. A 3-dimensional Look-Up-Table (LUT) is used to obtain the index key (Φ) from each pair of character components as shown by Eq. (2). K is the Look-Up function used for this purpose:

$$\Phi_{ij} = K(L_i, L_j, d_{ij}) \tag{2}$$

R-table contains the location of the hypothetical center of the seal model. We store the angle information ($\{\alpha_i, \alpha_j\}$) as function of Φ in the R-table. In Fig. 7 we show the representation of the seal model in a R-table.

In a seal all of the alpha-numeric character pairs (62×62) do not occur. So, keeping all combination of character pairs in that 3-dimensional LUT needs a huge memory. To reduce the memory space, we split the R-table in two different look-up-tables, e.g. character Pair (CP) table and Distance (D) table. In character pair table, all combination of alpha-numeric character pairs are computed. When we find a neighboring character pair (L_i, L_j) in a seal, a table (D_{ij}) for distance is linked with the neighboring character pair. The Distance table (D_{ij}) contains the angle information of corresponding character pairs. The size of CP table is $|L|^2$, where $|L|$ stands for the total number of text labels. Thus, the memory size of our R-table is ($|L|^2 \times D_l$), where D_l denotes the quantization parameter of the Distance table.

For each index key in R-table, there may be multiple entries of angle information due to the presence of many similar neighboring character pair in seals. The collision in R-table is resolved by chaining. In Fig. 8, we show the efficient data structure of the R-table. We also augment in R-table the model index along with angle information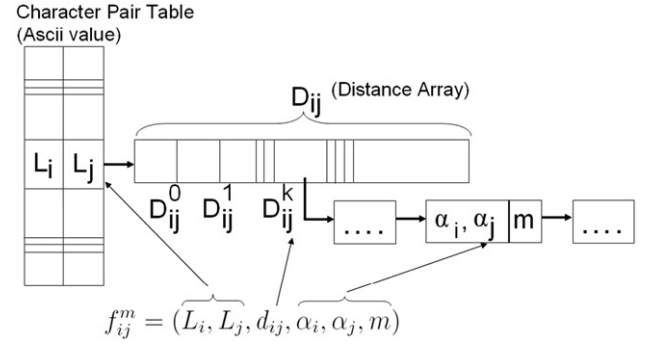. We explain the R-table construction process in Algorithm 1. Finally, all neighboring character pairs of model seals are compiled and added to the R-table. Thus an indexing scheme with all the seal models are constructed.

Algorithm 1. Seal description by local components.

Require: A model seal object (m) composed of components list $C_1 \ldots C_t$ and a Reference point R_m
Ensure: Seal representation by spatial organization of local components
  //Recognize character components
  for all C_i of $C_1 \ldots C_t$ **do**
    $L_i \Leftarrow$ Text Label of C_i
  end for
  //Find center of gravity (CG) of components
  for all C_i of $C_1 \ldots C_t$ **do**
    $G_i \Leftarrow$ CG of C_i **do**
  end for
  //create list of neighboring component pairs
  $P_m \Leftarrow \oslash$
  for all C_i of $C_1 \ldots C_t$ **do**
    $C_{i1} \ldots C_{in} \Leftarrow n-$nearest components of C_i
    for all C_j of $C_{i1} \ldots C_{in}$ **do**
      $P_m \cup (C_i C_j)$ if $(C_i C_j) \notin P_m$
    end for
  end for
  //record spatial information
  for all $(C_i C_j)$ from P_m **do**
    $d_{ij} \Leftarrow$ distance of (G_i and G_j)
    //Let Φ_{ij} be the index key
    $\Phi_{ij} \Leftarrow \{L_i, L_j, d_{ij}\}$
    $\alpha_i \Leftarrow \angle R_m G_i G_j$ and $\alpha_j \Leftarrow \angle G_i G_j R_m$
    $R[\Phi_{ij}] \Leftarrow R[\Phi_{ij}] \cup \{\alpha_i, \alpha_i \| m\}$
  end for

3.3. Isolated seal recognition

Although the final purpose is the retrieval of document images from a database, we present here GHT-based approach for classifying isolated seal images to better assess the performance of the recognition approach. To recognize isolated seal images, we first construct the R-table with a set of model seals. Next, the text components from the isolated query seal image are extracted using a text/graphics separation system. The local features are computed by spatial descriptor from each pair of characters in that seal as explained before. Here, the reference point is selected in the same way as the centre of minimum enclosing circle (MEC) of the seal. The character components provide high level spatial descriptor. For each neighboring character pair, we compute the index key (Φ) as given in Eq. (2). Next, all the angle information corresponding to each neighboring character pair and their distance are retrieved from the R-table. These angles are compared to the angle information of each neighboring character pair of query seal. If difference of these two angles are less than T_α, we say a matching is occurred. The value of T_α ($= 1°$) is set up empirically.

For recognition purpose, we create a table of all the model seals and initialize all with 0 s. The counter of seal class is incremented whenever a matching entry of angle is found in the R-table. Finally, the classes are ranked in descending order with the number of voting. The model seal for which we get highest number of votes is selected as the recognized one for that corresponding sample.

3.4. Seal detection in document database for retrieval

To detect seals in a document image, at first, a R-table is created from a set of predefined model seals. Model seals are segmented manually so that only the text characters present in the seal part can be used in the R-table. The construction of the R-table is performed to record all spatial description of neighboring character pairs of each model seal as discussed in Algorithm 1. The constructed R-table will be used later to find hypothesis of the seal models in a document. For seal detection from an input document, we considered all characters paired with their n-nearest neighbors and based on information of the n-neighboring component pair using
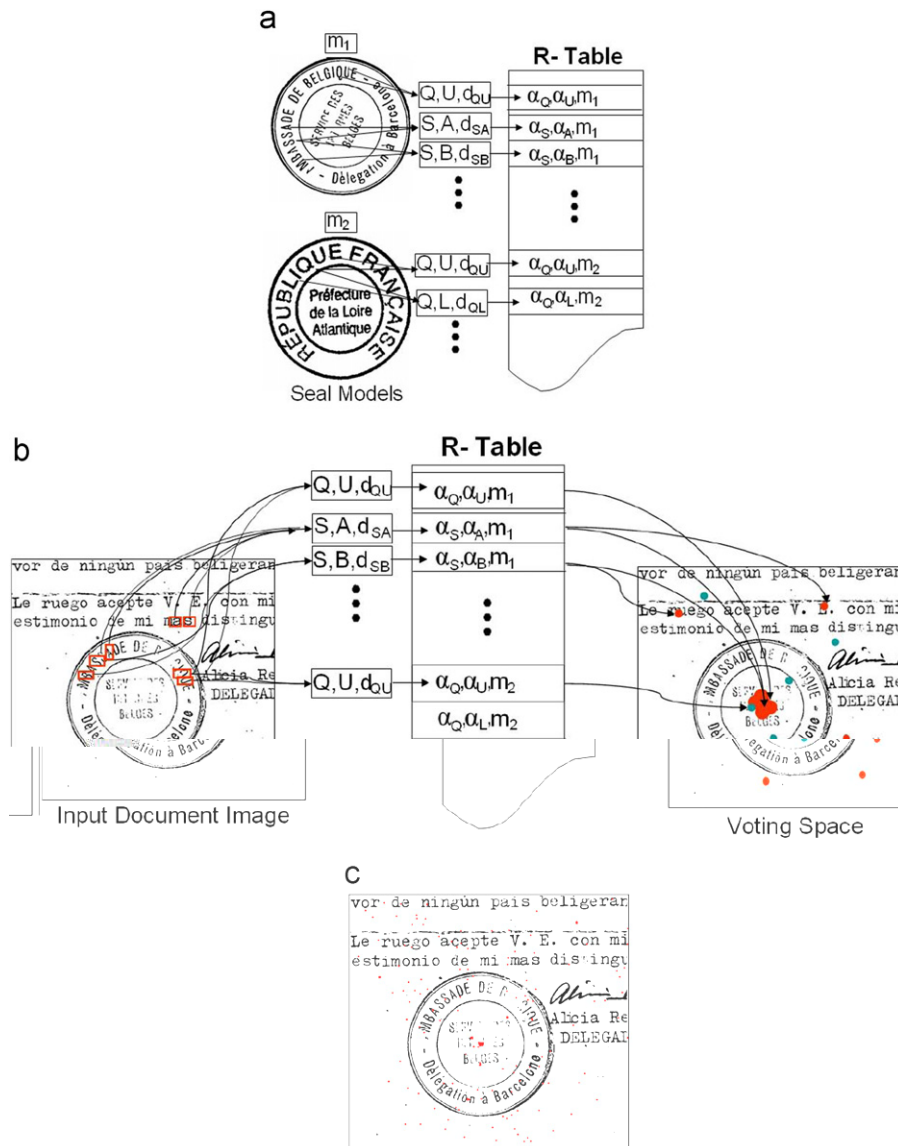

Fig. 9. (a) Construction of R-table from two seal models m_1 and m_2 for GHT, (b) Hypothesis of Reference Point of seals are obtained from models' R-table. Red and green colors in voting space indicate the hypothesis of model m_1 and m_2, respectively (designed synthetically) and (c) Voting areas (Red color) in document after running the seal detection algorithm with the query seal m_1 of (a). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

R-table, we cast vote for the hypothetical location of seal model. For a neighboring component pair (C_i and C_j) of the document, we compute L_i, L_j and distance d_{ij} between their CGs. Using this spatial feature corresponding to the neighboring component pair, the hypothetical location and seal model information are obtained. To achieve the hypothetical location, we obtain the index key Φ (see Eq. (2)) for each pair of text character. Next we extract all the hypothesis of the spatial angle information and model index from R-table using

$$\{(\alpha_i, \alpha_j, m)\} \Leftarrow R(\Phi_{ij}) \tag{3}$$

These angle information (α_i, α_j) provide the location of hypothetical centre of the seal model (m). In our process, we cast votes in both directions relative to character pair and the voting is performed in pixel level. We show this process using a diagram in Fig. 9. This voting mechanism accumulates evidences in the locations where we find the similar neighboring component pair having same spatial distance.

The presence of a particular seal in document produces peaks in the GHT voting space. Since, we vote in pixel level, the peak is obtained by finding zones of high vote density. The more we find the matching of neighboring character pair descriptor, the more accumulation of voting will be there. Finally, we detect the existence of the query seal using number of votes in local peaks of accumulation space. The presence of seal in a document is thus determined by searching total votes in each peak of the accumulator. The number of votes is normalized by the total number of spatial features of the corresponding seal model. If f_m be the total number of spatial features of the query seal and f_d be the number of votes found in peak then we compute f_d/f_m. If this value is greater than T_m, then we accept the presence of the query seal in the document. The value of T_m ($=0.3$) is set up experimentally. In Fig. 9, we show an example of voting procedure from our seal models. Fig. 9(a) shows the construction of R-table from two seal models m_1 and m_2 with different neighboring character pairs. In Fig. 9(b), we show how hypothetical locations are obtained from R-table from the character pairs of documents. Fig. 9(c) shows a real output of voting regions after running the seal detection algorithm with a query seal m_1 of Fig. 9(a).

4. Experimental results

As application scenario, the approach described here has been applied to the historical archive of border records from the Civil Government of Girona [20]. It consists of printed and handwritten documents between 1940 and 1976. The documents are related to people going through the Spanish-French border. These documents are organized in personal bundles. For each one, there is a cover page with the names of people whose information is contained in this record. In each bundle there is very diverse documentation, so we can find safe-conduct to cross the border, arrest reports, information of professional activities, documents of prisoners transfer to labor camps, medical reports, correspondence with consulates, telegram, etc. This documentation has a great importance in the studies about historical issues related with the Spanish Civil War and the Second World War. From the digital archive of scanned document images it is interesting to extract information regarding people (names, nationality, age, civil status, dates, location of arrest, etc.) that can be used for indexing purposes. Depending on the location of office of registration, the documents contain different types of seal. The documents were scanned in 200 dpi and stored in binary form. The documents are written in English and the seals posted on these documents also contain English text characters. Our seal spotting method has been applied to retrieve the bundle of documents which got registered using similar seal. Two experiments have been designed to evaluate the performance of our approach. First experiment is done to check the performance of isolated seal recognition. The other test is performed on a historical

archive to detect the seal and retrieve the related documents based on seal information. Before demonstrating the experimental results, we show the performance evaluation of text characters recognition using different shape descriptors. This is done since character labels obtained through text recognition are used in the GHT step of seal detection.

4.1. Performance of text character recognition

The seal images in our dataset contain multi-oriented text characters. As discussed earlier, seals are affixed in documents in arbitrary rotation. Moreover, due to digitization process into binary level, generally the images contain noise and text characters get degraded many times. Thus, text character recognition is a challenging task in such environment. To overcome such problems, multi-scale and multi-rotation shape features are used as discussed in Section 2. SVM classifier is employed for isolated text character recognition in seal documents. Different kernel functions such as Polynomial kernels, Sigmoid kernels, Gaussian kernels, etc. [36] can be found in the literature. We tested SVM with different kernels on our dataset and the results are given in Table 3. It can be noted that, as similar shaped text characters are grouped in the same class, the variation among different classes is increased. So, the classifiers with different kernels show similar results. The SVM with Gaussian kernels showed the highest performance among different kernels. Thus, Gaussian kernel with radial basis function (RBF) has been chosen in our experiments to recognize multi-oriented text characters due to its superiority.

For the sake of evaluation, a comparison is done with different feature descriptors, e.g. angle-based features, ART, Hu, Zernike moments and Fourier Mellin explained in literature. We considered a set of data consisting of multi-oriented and multi-scale text characters to perform this character recognition evaluation. Since, text characters of different fonts are to be recognized before feeding to GHT, we train characters of different fonts which are considered not only from seal but also from other documents like maps, graphical documents, etc. The size of the dataset is 8250 and the dataset contains ground-truth. A text separation method [31] has been used to extract characters from these documents towards the development of this dataset. The groundtruth of this dataset has been generated manually for the performance evaluation. The feature vectors obtained from different descriptors are passed to a SVM classifier to get the recognition accuracy. The classification is done in 5-fold cross-validation way. To do that, the dataset is divided into five subsets of which four subsets were used for training and rest for testing. This process is repeated five times so that all the five subsets can be tested. The recognition rates obtained from all the five test subsets were averaged to get 5-fold cross validation accuracy. Their performance and comparative results are shown in Table 4. It is noted that, angle-based features

Table 3
Comparison of performance of SVM using different kernel functions.

Linear (%)	Polynomial (%)	RBF (%)	Sigmoid (%)
98.70	98.84	98.89	86.58

Table 4
Text character recognition accuracy with different shape feature descriptors.

ART (%)	Hu moment (%)	Zernike moment (%)	Fourier Mellin (%)	Angle-based approach (%)
89.06	61.71	90.19	96.52	98.89

and Hu moments are best and least performers among these features to classify text characters.

4.2. Performance of isolated seal recognition

Though our objective is to detect the query seal in a given document, we will discuss here the pros and cons of our GHT-based approach to recognize isolated seal symbols. We will also compare the performance of this local character-based approach with other pixel-based approaches found in literature. For the experiment, we have created a database of isolated seals to test the seal recognition approach irrespective of isolated character recognition. This database contains 220 isolated seal images of 19 different classes. The seals are initially extracted automatically from the archive using large components extraction method. This method may detect large components such as logo, signature, etc. Next, a manual checking is done to consider only the seal shapes. The seals are of different shapes and rotations. In our database there are mainly three types of seal shape, e.g. circular, elliptical and rectangular. We noted that the seals contain different number of text characters for their description. The numbers of text characters present in each type of 19 classes of seal are detailed in Fig. 10. Maximum (minimum) number of characters are obtained in the seal of class 14(3) and it contains 83(16) characters. Different types of seals (elliptical, circular, rectangular) in the database are marked by different color in this figure.

To get an idea of quality of data used in our experiment, some samples of the data are shown in Fig. 2. From the figure, it can be seen that although the seals are having similar boundary (e.g. circular, elliptical), the text information within them are different. From the experiment we noted that our method can tackle this kind of images. To assess the usefulness of text information in seals, initially we performed a direct global classification test to the seal dataset at pixel level as features. In this experiment text identification are not used to evaluate the effectiveness of our GHT-based approach. Here, we consider the whole seal as a symbol of texture
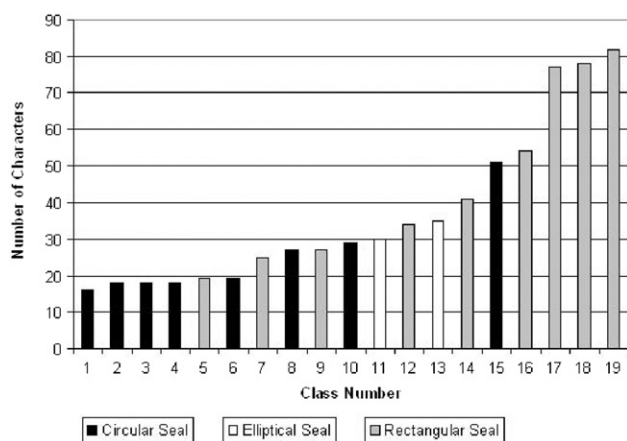
only and different feature descriptors are applied to recognize such texture-based symbol objects. The classification is performed using different rotation invariant shape descriptors. To get the idea of recognition results of different rotation invariant descriptors, we present a comparative study on this dataset with different descriptors like (a) ART, (b) Hu, (c) Zernike (Zn), (d) Fourier–Mellin, (e) angle-based approach and (f) shape context. The features obtained from each shape descriptors are fed to a classifier for matching. A model (prototype) seal for each class is selected. These models are chosen according to cross-validation scheme. We have used Euclidean distance-based measures for this purpose. We measure the distance for each data from each model. Next, we assign the level of the model to the data according to minimum distance. In Table 5, we show the recognition accuracy obtained using different shape descriptors at different coarse level (up to five choices). From the experiment we noted that Zernike moment feature descriptor performs better than other descriptors in fine level (top 1 choice). When we increase the number of top choices, the difference of recognition accuracy between angle-based approach and Zernike moment decreases. When five top choices are considered, angle-based approach gives better result than Zernike.

For one top choice, the highest performance of seal recognition considering seal as a whole symbol is only 50.22% and this is obtained from Zernike moment. This lower performance is because, global pixel-based shape descriptors are not enough to discriminate them properly. Seal defines a symbol description with its rich internal textual structure. It contain a bigger boundary frame and smaller text components. The confusion arises between the seal shapes which have similar boundary shapes. The text characters which convey the major information in seal are not represented well in general pixel level shape descriptor.

Next, we test the recognition of isolated seals using the GHT approach described earlier. The recognition is performed using local features computed from text characters (small components) of seal only. The text characters are labeled using SVM. The outer frame and other long graphical lines of seal are not considered. To have an idea about the effectiveness of our method on poor images, we show some noisy seal images in Fig. 11(a), where our method performed correctly. We also have shown examples in Fig. 11(b) where our method failed. Here, in the first seal image, many of the characters are overlapped with long graphical lines. After separating text characters using text separation algorithm, these text characters were not extracted, so the proper seal model is not found for this sample. In 2nd seal, many text characters are missing in the input sample. In 3rd seal, many characters are broken and overlapped with other text (it may happen while pressing the seal). Since, our method is based on component level, if characters are broken the method may not work properly.

Using GHT, we have obtained 92.42% accuracy on seal recognition considering characters are labelled by angle-based features. We show the seal recognition results using different number of top choices in Table 6. The choices are considered based on number of accumulated votes in different classes of seals. We obtained upto 98.58% accuracy when top 5 choices are considered (coarse level recognition). We have also tested the seal recognition using text characters labelled by other shape descriptors namely Hu moments
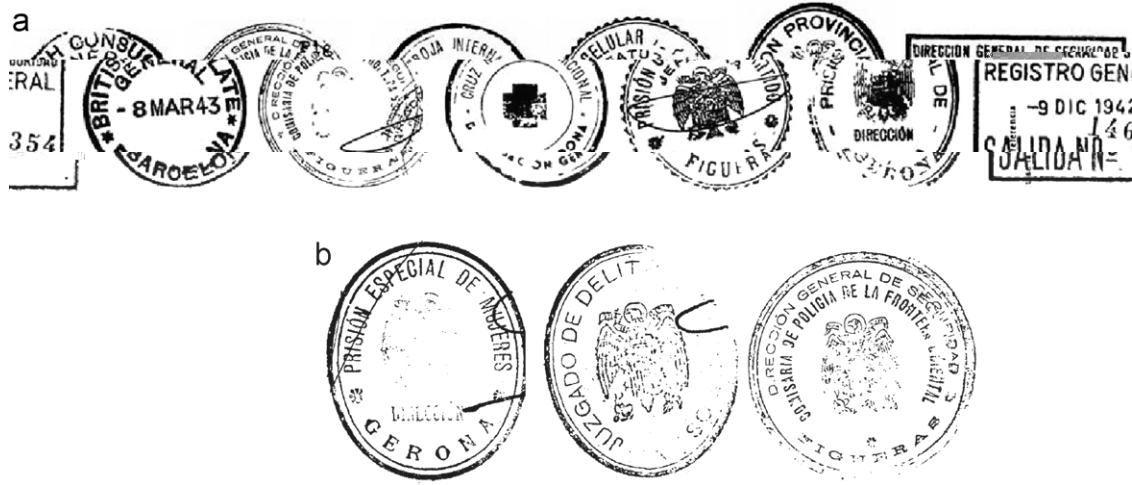

Fig. 10. Number of text characters present in 19 different classes of seals are shown.

Table 5
Comparison of seal (as a single symbol) recognition accuracy of different approaches.

Number of top choices	ART (%)	Hu moment (%)	Zernike moment (%)	Fourier Mellin (%)	Angle-based approach (%)	Shape context (%)
1 choice	< 5	< 10	50.22	< 5	36.65	24.89
2 choices	< 5	< 10	68.72	< 5	60.18	56.61
3 choices	22.74	10.42	73.63	< 5	69.19	63.42
4 choices	27.01	19.43	79.14	< 10	73.93	70.36
5 choices	30.33	24.64	83.41	12.32	83.89	78.57

Fig. 11. Some examples of noisy isolated seals recognized correctly (a) and wrongly (b) by our approach.

Table 6
Seal recognition accuracy using GHT by local connected components.

Number of top choices	Angle-based approach (%)	Hu moment (%)	Zernike moment (%)
Only 1 choice	92.42	62.12	73.68
Only 2 choices	96.68	73.94	82.61
Only 3 choices	97.16	80.56	85.37
Only 4 choices	98.11	83.88	88.56
Only 5 choices	98.58	87.21	91.78

Table 7
Seal Recognition accuracy according to different boundary shapes by our proposed approach.

Rectangular (%)	Circular (%)	Elliptical (%)
93.61	91.74	87.50

Fig. 12. Seal pairs where confusion occurred.

seal where it finds maximum text character-based spatial matching, which is another advantage of our approach.

4.3. Performance of seal detection result

To test the seal detection approach, we have constructed a database with 370 documents containing seals of English text characters. The database sometimes contains document images in up side down way. The seals are posted in different orientation and in different locations of these documents. There were missing of some seal information many times by noise or overlapped signature. Sometimes, due to posting seal on text document, additional text characters of document are also placed inside the seal region. We have considered additional 160 documents in this dataset which do not have the seals. Thus, our seal dataset consisted of 530 documents having different complexity.

In our experiment, here at first, we have provided some qualitative results to show how query seals are detected in documents with our approach. Next, we evaluate the performance of seal detection in the dataset of our experiments with precision-recall curve. We compared the seal detection results using three different multi-oriented text descriptors namely: angle-based approach, Zernike moments and Hu moments. We have also discussed the performance of seal detection method based on the selection of different number of neighboring character pairs. We also provide a comparative result with patch-based descriptors like SIFT and shape context. Finally, we give an idea of the computation time of different methods we tested here.

In Fig. 13, we show seal detection results of our approach when four different documents are tested. We used angle-based features and SVM to classify text characters. As explained before, the location of a query seal is detected in these documents by our GHT approach. To visualize the detection results, we draw a circle of
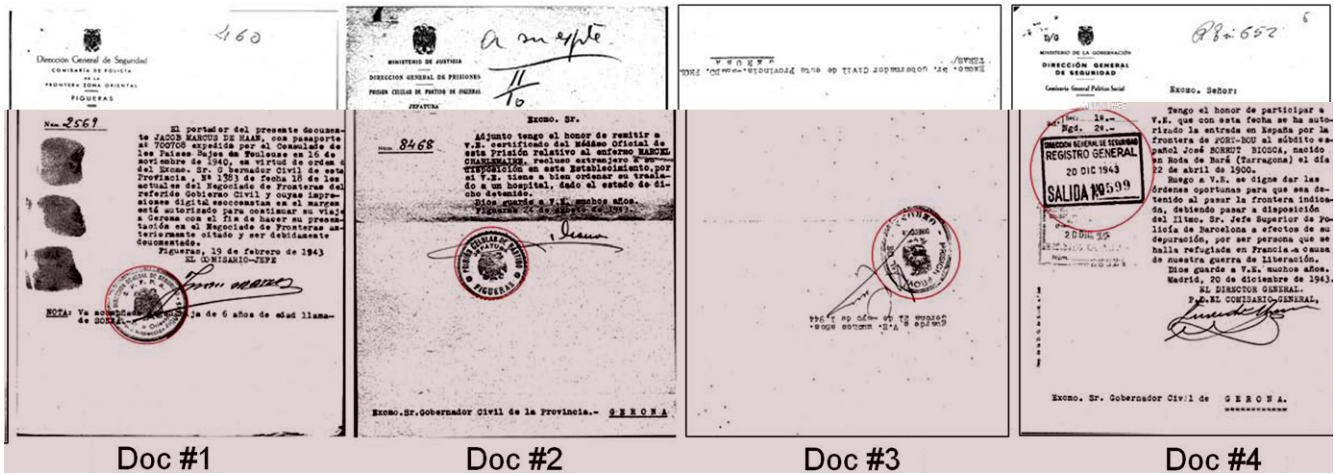
and Zernike moments descriptors. These results are also shown in Table 6 to compare how different text recognition labelling can affect the seal recognition. To get the idea of the recognition accuracy according to different shapes of seal (though this boundary information is not considered in our approach) we show the results of our proposed method in Table 7. The recognition results depict that, the proposed approach is not sensitive to the text strings' global position, i.e. whether the strings are posted within seal in linear or curve way. As explained before, the recognition is done based on number of votes for each class. When we rejected 13.12% of samples based on less votes for recognized class, we got 95.31% accuracy using first choice only.

From the experiment we noticed that most of the errors occur because of the presence of similar text string in some of the seals. The pair of seal models from which main confusion occurred are shown in Fig. 12. Here, we see in both of the seals, the string "DIRECCION GENERAL DE SEGURIDAD" exist apart from other text lines. Though the font styles are different, we get similar information from the strings using SVM classifier. Due to noise, when other string characters are not recognized properly, we get similar voting for these models. The confusion rate obtained from these seals pair is found to be 1.37% when it is computed from overall samples of the dataset. This confusion arises mainly due to unavailability of expected text information from seal. In this kind of images unlike pixel-based systems our approach searches for the possible model

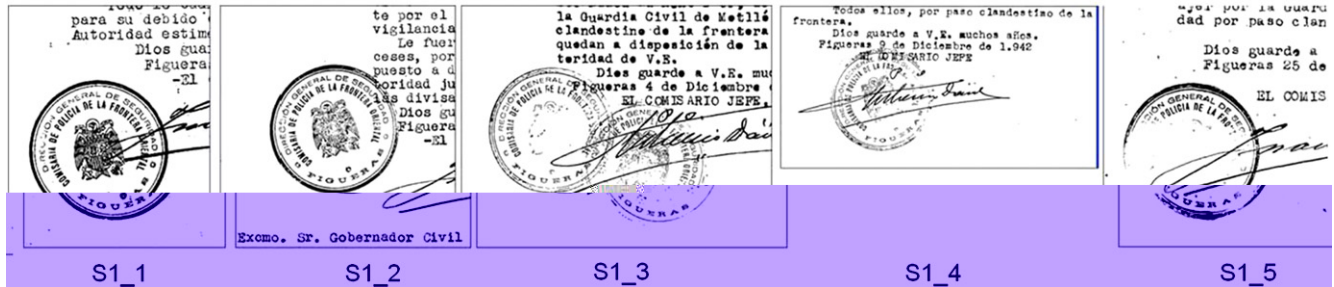**Fig. 13.** Detection of seals in documents.

Fig. 14. Ranking of different documents of a seal model.

radius of *MEC* of the query seal in that particular location. It is appreciable to see that our seal recognition performs well when there exists signature or other text overlapping with seal region. Here, Doc#1 and Doc#2 have two different seals though they share similar shape structure (circle). Using our approach, we correctly distinguish them and label the associate seal model with it. In Doc#3, it is shown that the query seal is detected in the document in spite of 180 degree rotation of the document. In Doc#4, a date was affixed during stamping and because of this, seal region contained additional alpha-numeric characters. We noted that, our approach can detect the seal from these documents having variable date field in the seal region.

Given a query seal image, a ranked list of retrieved documents from our database are shown in Fig. 14. The ranking is done based on voting in accumulation array. It is understandable from the ranking of these images, how noise, overlapping and occlusion do affect the ranking process. Here, we show five results of the ranked documents, retrieved by querying a seal model. We see, in Fig. 14(S1_3), a seal was affixed 2 times and they have some overlapped portions. In Fig. 14(S1_5), the approach could detect the seal although there were many text characters missing. Since our method works considering only labeled text characters, we can use this to detect arbitrary shape of seal and this is one of the advantages of our method.

To evaluate the quantitative performance of the system with a query seal against a collection of documents, we use common ratio of precision (*P*) and recall (*R*) for evaluation of retrieval of documents. In the retrieved documents, the results are ranked by the number of votes. Each retrieved document is considered as relevant or not depending on the ground truth of the data. The precision measures the quality of the retrieval system in terms of the ability of the system to include only relevant items in the result. Whereas recall measures the effectiveness of the system in retrieving the relevant items. Precision and Recall computation formula are as follows:

$$P = \frac{\|retrieved \cap relevant\|}{\|retrieved\|}, \quad R = \frac{\|retrieved \cap relevant\|}{\|relevant\|}$$

In Fig. 15(a), we compare the performance of seal detection system using three different character shape features, namely angle-based approach, Zernike moment and Hu moment. The precision and recall plot shown in Fig. 15 is computed as follows. Based on the number of votes for each query seal image in GHT accumulator, the retrieved documents are ranked. Next, ranked documents obtained from all the query seals are averaged and this average ranking is used in precision and recall plot computation. We consider the averaged ranked results into ten parts (first 10%, first 20%, …first 90% and 100%) and precision and recall plot is computed based on the results of these 10 parts. Finally, we interpolated the results of the precision and recall plot.

The precision is obtained 100% using these features during the recall value until 20%. Then the performance on Hu and Zernike moments-based seal retrieval got reduced. As we explained in Tables 4 and 6, the reason of lower performance of seal detection is the poor shape feature descriptor of text characters.

It is mentioned in Section 3.4 that a list of neighboring character pairs are found from each text component using its *N* nearest neighbors. In Fig. 15(b) we show the average precision and recall plot of a query seal model in the whole database using different number of neighbor component selection of our proposed approach. The selection of number of neighbor character is checked because, the spatial organization of the neighboring character pair depends on this criterion and based on each character pair, the location of hypothe-
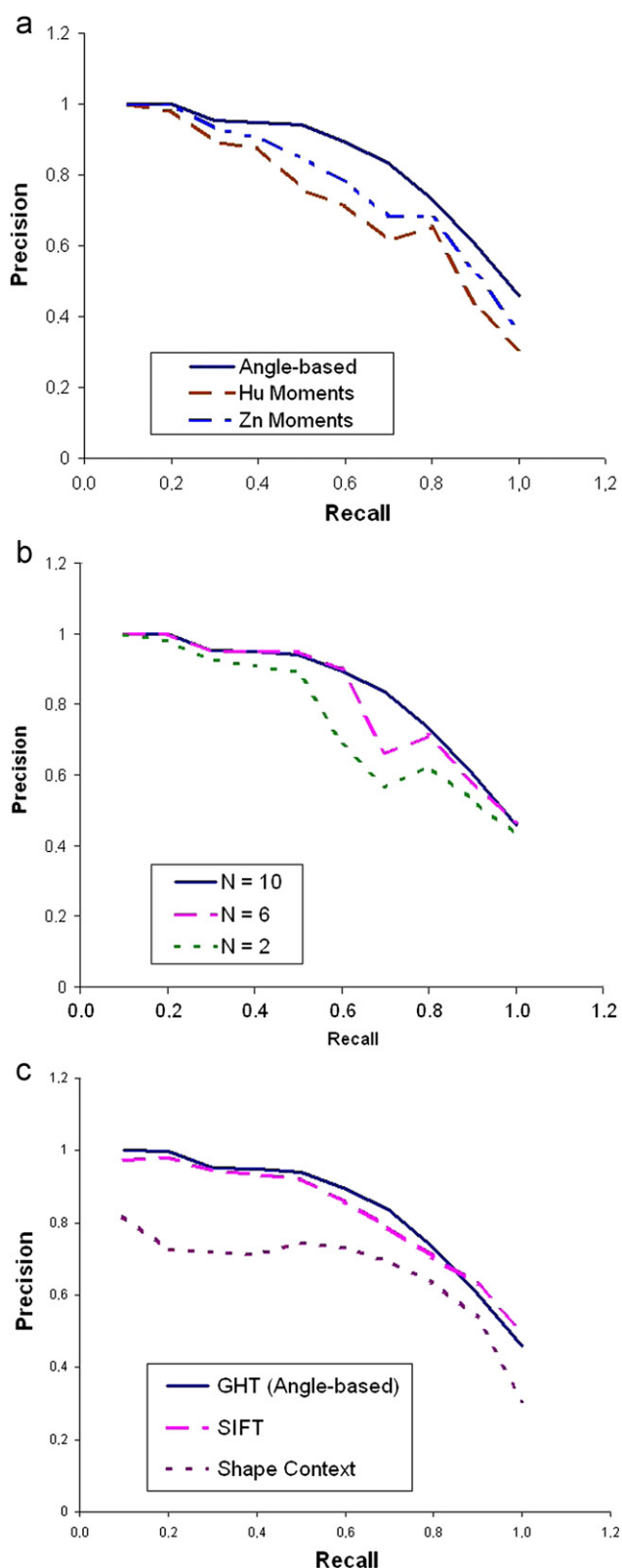
Fig. 15. Precision-recall curve of document retrieval using different: (a) character recognition features, (b) choice of neighbor and (c) other patch-based method.

Table 8
Computation time (in seconds) of seal detection system.

Patch-based descriptor		Text-based descriptor		
SIFT	Shape context	Hu moment	Zernike moment	Angle-based approach
2.1	2.7	3.3	3.9	3.4

broken or touched with graphical lines. If the local text characters are not segmented or labeled correctly, our method may not work properly. When we use less number of neighboring character pairs, it may fail due to improper hypothesis generation. Hence, a valley appears in the precision-recall curve (Fig. 15(b)). When the choice of neighboring characters are more, the system is benefited from the other text characters (far neighbour) and the proposed approach is able to improve its performance based on the spatial relationships of other characters. Hence, with more neighboring character pairs, our system has more strength to detect the seal in such documents and thus the valley slowly vanishes.

We have compared our result with well known features like SIFT [21], shape context [4]. In Fig. 15(c) we show the average precision and recall plots of seal detection results obtained from our database. The procedures to detect seals using these descriptors are designed as follows. A Harris corner detector is used to detect the invariant key points. RANSAC fitting algorithm [9] is then used to filter some false matches. From the result, it is noticed that the seal detection approach based on local character recognition shows better precision accuracy than other methods till 90% recall of the dataset. After that, recognition of text characters within seal fails due to noise. So, the precision accuracy curve of seal detection of angle-based approach falls rapidly. Shape context did not provide good result in the experiment.

The performance of seal detection approach using text component extraction found better than patch-based descriptors like SIFT. It is to be noted that using text character-based seal detection scheme, we also have a semantic layer among the text characters in the seal. The text string found using recognized characters can provide a description of seal which is an added advantage of our approach.

Finally, we give an indication about the system's computation time. When testing the 530 documents in seal dataset for a query seal, the proposed method spent approximately 3.4 seconds on an average to detect seal in each document (by a PC of 2.00-GHz T6400 Intel Core 2 Duo Processor). In Table 8 we compare the approximate processing time to run the same using different approaches.

5. Conclusion

In this paper, we have presented a seal detection approach based on spatial arrangement of seal content. A query seal is translated into a set of spatial feature vector using its text character information. These features are used later to locate a seal of similar content in documents. We have used a multi-oriented and multi-scale text character recognition method to generate high level local feature to take care of complex multi-oriented seal information. The recognition result of these character components within seal region is used to generate local spatial information to classify and detect the seal. Relative positional information of text string characters are used for this purpose and hypothesis were generated based on that.

The existing systems of seal detection approach consider the seal as a whole object. Use of rotation invariant features [24] to recognize whole seal may not work properly for the seals which are having similar boundary frames, frequent missing of text characters or inclusion of background text characters. The approaches [38] based on seal frame detection cannot recognize the seal type in

tical reference point is voted. So, the more we select the number of neighboring character pair for each character, the higher the performance of the document retrieval system.

As discussed before, the documents in the historical dataset are sometimes degraded and as a result the text characters are

the document. Also, color-based approaches [35] will not work for degraded binary images. Our approach of seal detection based on GHT of local text characters overcome such problems efficiently. Moreover, our approach can detect the seal even if all the characters from the seal are not extracted.

We tested our method in a database of multi-oriented seal documents containing noise, occlusion and overlapping. In retrieval of document image from database, all components of a document pass through the recognition process and hence it is time consuming. So, the improvement of the performance in terms of time could be achieved if a pre-processing method (run-length smoothing) is applied to remove non-seal information from the document. Also the use of boundary-shape information (circular, rectangular, etc.) of seal may improve it further.

References

[1] S. Adam, J.M. Ogier, C. Carlon, R. Mullot, J. Labiche, J. Gardes, Symbol and character recognition: application to engineering drawing, International Journal on Document Analysis and Recognition (IJDAR) 3 (2000) 89–101.
[2] D. Ballard, Generalizing the Hough transform to detect arbitrary shapes, Pattern Recognition 13 (2) (1981) 111–122.
[3] D. Baumann, S. Ranka, The generalized Hough transform on an MIMD machine, Journal of Undergraduate Research in High-Performance Computing 2 (1992) 1–8.
[4] S. Belongie, J. Malik, J. Puzicha, Shape matching and object recognition using shape contexts, IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (4) (2002) 509–522.
[5] Y.S. Chen, Automatic identification for a chinese seal image, Pattern Recognition 29 (1996) 1807–1820.
[6] Y.S. Chen, Registration of seal images using contour analysis, in: Scandinavian Conferences on Image Analysis (SCIA), 2003, pp. 255–261.
[7] J.Y. Chiang, R. Wang, Seal identification using the Delaunay tessellation, in: Proceedings of National Science Council ROC (A), vol. 2, 1998, pp. 751–757.
[8] R. Datta, D. Joshi, J. Li, J.Z. Wang, Image retrieval: ideas, influences, and trends of the new age, ACM Computing Surveys 40 (2) (2008) 1–60.
[9] M.A. Fischler, R.C. Bolles, Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography, Communications of the ACM 24 (6) (1981) 381–395.
[10] A.S. Frisch, The fuzzy integral for color seal segmentation on document images, Proceedings of International Conference on Image Processing ICIP, vol. 1, 2003, pp. 157–160.
[11] W. Gao, S. Dang, X. Chen, A system for automatic chinese seal imprint verification, Proceedings of International Conference on Document Analysis and Recognition (ICDAR), vol. 2, 1995, pp. 660–664.
[12] R. Haruki, T. Horiuchi, H. Yamada, K. Yamamoto, Automatic seal verification using three-dimensional reference seals, Proceedings of the 13th International Conference on Pattern Recognition (ICPR), vol. 3, 1996, pp. 199–203.
[13] T. Horiuchi, Automatic seal verification by evaluating positive cost, in: Proceedings of International Conference on Document Analysis and Recognition ICDAR, 2001, pp. 572–576.
[14] M.-K. Hu, Visual pattern recognition by moment invariants, IRE Transactions on Information Theory IT 8 (1962) 179–187.
[15] Q. Hu, J.Y. Yang, Q. Zhang, K. Liu, X. Shen, An automatic seal imprint verification approach, Pattern Recognition 28 (1995) 1251–1266.
[16] J. Iivarinen, A. Visa, Shape recognition of irregular objects, in: Intelligent Robots and Computer Vision XV: Algorithms, Techniques, Active Vision, and Materials Handling, Proceedings of SPIE, vol. 2904, 1996, pp. 25–32.

[17] A. Khotanzad, Y. Hong, Invariant image recognition by Zernike moments, IEEE Transactions on Pattern Analysis and Machine Intelligence 12 (1990) 489–497.
[18] S.W. Lee, J. Kim, Attributed Stroke graph matching for seal imprint verification, Pattern Recognition Letter 9 (1989) 137–145.
[19] H. Liu, Y. Lu, Q. Wu, H. Zha, Automatic seal image retrieval method by using shape features of chinese characters, in: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, 2007, pp. 2871–2876.
[20] J. Lladós, D. Karatzas, J. Mas, G. Sanchez, A generic architecture for the conversion of document collections into semantically annotated digital archives, Journal of Universal Computer Science 14 (2008) 2912–2935.
[21] D.G. Lowe, Distinctive image features from scale-invariant keypoints, International Journal of Computer Vision 60 (2004) 91–110.
[22] S. Lu, C.L. Tan, Retrieval of machine-printed latin documents through word shape coding, Pattern Recognition 41 (5) (2008) 1816–1826.
[23] T. Matsuura, K. Mori, Rotation invariant seal imprint verification method, in: Proceedings of Ninth International Conference of Electronics, Circuits & Systems, vol. 3, ICECS, 2002, pp. 955–958.
[24] T. Matsuura, K. Yamazakiv, Seal imprint verification with rotation invariance, Circuits and Systems 1 (2004) 597–600.
[25] T. Nakai, K. Kise, M. Iwamura, Camera-based document image retrieval as voting for partial signatures of projective invariants, in: Proceedings of International Conference on Document Analysis and Recognition (ICDAR), Washington, DC, USA, 2005, pp. 379–383.
[26] F. Nourbakhsh, P.B. Pati, A.G. Ramakrishnan, Automatic seal information reader, in: Proceedings of International Conference on Computing: Theory and Applications (ICCTA), 2007, pp. 502–505.
[27] L. O'Gorman, The document spectrum for page layout analysis, IEEE Transactions on Pattern Analysis and Machine Intelligence 15 (11) (1993) 1162–1173.
[28] T. Rath, R. Manmatha, Word spotting for historical documents, International Journal on Document Analysis and Recognition (IJDAR) 9 (2005) 139–152.
[29] J. Ricard, D. Coeurjolly, A. Baskurt, Generalizations of angular radial transform for 2d and 3d shape retrieval, Pattern Recognition Letters 26 (2005) 2174–2186.
[30] P.P. Roy, U. Pal, J. Lladós, M. Delalandre, Multi-oriented and multi-sized touching character segmentation using dynamic programming, in: Proceedings of the International Conference on Document Analysis and Recognition (ICDAR), Barcelona, Spain, 2009, pp. 11-15.
[31] P.P. Roy, E. Vazquez, J. Llados, R. Baldrich, U. Pal, A system to segment text and symbols from color maps, Graphics Recognition, Recent Advances and New Opportunities: Seventh International Workshop, GREC Selected Papers, 2008, pp. 245–256.
[32] M. Rusinol, J. Lladós, Word and symbol spotting using spatial organization of local descriptors, in: Proceedings of International Workshop on Document Analysis Systems (DAS), 2008, pp. 489–496.
[33] K. Tombre, B. Lamiroy, Graphics recognition—from re-engineering to retrieval, in: Proceedings of International Conference on Document Analysis and Recognition (ICDAR), 2003, pp. 148–155.
[34] K. Tombre, S. Tabbone, L. Peissier, B. Lamiroy, P. Dosch, Text/graphics separation revisited, in: Proceedings of International Workshop on Document Analysis Systems (DAS), 2002, pp. 200–211.
[35] K. Ueda, T. Mutoh, K. Matsuo, Automatic verification system for seal imprints on Japanese bankchecks, in: Proceedings of International Conference on Pattern Recognition (ICPR), 1998, pp. 629–632.
[36] V. Vapnik, The Nature of Statistical Learning Theory, Springer Verlag, 1995.
[37] G. Zhu, D. Doermann, Logo matching for document image retrieval, in: Proceedings of International Conference on Document Analysis and Recognition (ICDAR), 2009, pp. 606–610.
[38] G. Zhu, S. Jaeger, D. Doermann, A robust stamp detection framework on degraded documents, in: Proceedings of SPIE Conference on Document Recognition and Retrieval, 2006, pp. 1–9.

Partha Pratim Roy has obtained Ph.D. in 2010 from Universitat Autònoma de Barcelona, Spain. He received his Bachelor of Technology degree in Computer Science in 2002 from Kalyani University in India. From 2003 to 2005, he was working as an Assistant System Engineer in Tata Consultancy Services. He obtained his MS in Computer Vision and Image Processing in 2007 from Universitat Autònoma de Barcelona. His research work focuses on the analysis of text/symbol present in graphical documents. It includes understanding of text graphics separation from graphical documents and recognition of text/graphics in multi-scale and multi-orientation environment.

Umapada Pal received his Ph.D. from Indian Statistical Institute and his Ph.D. work was on the development of Printed Bangla OCR system. He did his Post Doctoral research on the segmentation of touching English numerals at INRIA (Institut National de Recherche en Informatique et en Automatique), France. During July 1997–January 1998 he visited GSF-Forschungszentrum fur Umwelt und Gesundheit GmbH, Germany to work as a guest scientist in a project on image analysis. From January 1997, he is a Faculty member of the Computer Vision and Pattern Recognition Unit, Indian Statistical Institute, Kolkata. His primary research is Digital Document Processing. He has published 163 research papers in various international journals, conference proceedings and edited volumes. In 1995, he received student best paper award from Chennai Chapter of Computer Society of India. He received a merit certificate from Indian Science Congress Association in 1996. Because of his significant impact in the Document Analysis research domain of Indian language, TC-10 and TC-11 committees of IAPR (International Association for Pattern Recognition) presented 'ICDAR Outstanding Young Researcher Award' to Dr. Pal in 2003. In 2005–2006 Dr. Pal has received JSPS fellowship from Japan government. Dr. Pal has been serving as a program committee member of many conferences including International Conference on Document Analysis and Recognition (ICDAR), International Workshop on Document Image Analysis for Libraries (DIAL), International Workshop on Frontiers of Handwritten Recognition (IWFHR), International Conference on Pattern recognition (ICPR) etc. Also, he is the Asian PC-Chair for 10th ICDAR to be held at Barcelona, Spain in 2009. He has served as the guest editor of special issue of VIVEK journal on Document image analysis of Indian scripts. Also currently he is co-editing a Special issue of the journal of Electronic Letters on Computer Vision and Image Analysis. He is a life member of IUPRAI (Indian unit of IAPR) and senior life member of Computer Society of India.

Josep Lladós received the degree in Computer Sciences in 1991 from the Universitat Politècnica de Catalunya and the Ph.D. degree in Computer Sciences in 1997 from the Universitat Autònoma de Barcelona (Spain) and the Universitè Paris 8 (France). Currently he is an Associate Professor at the Computer Sciences Department of the Universitat Autònoma de Barcelona and a staff researcher of the Computer Vision Center, where he is also the director since January 2009. He is the head of the Pattern Recognition and Document Analysis Group (2009SGR-00418). He is chair holder of Knowledge Transfer of the UAB Research Park and Santander Bank. His current research fields are document analysis, graphics recognition and structural and syntactic pattern recognition. He has been the head of a number of Computer Vision R+D projects and published more than 100 papers in national and international conferences and journals. J. Lladós is an active member of the Image Analysis and Pattern Recognition Spanish Association (AERFAI), a member society of the IAPR. He is currently the chairman of the IAPR-ILC (Industrial Liaison Committee). Formerly he served as chairman of the IAPR TC-10, the Technical Committee on Graphics Recognition, and also he is a member of the IAPR TC-11 (reading Systems) and IAPR TC-15 (Graph-based representations). He serves on the Editorial Board of the ELCVIA (Electronic Letters on Computer Vision and Image Analysis) and the IJDAR (International Journal in Document Analysis and Recognition), and also a PC member of a number of international conferences. He was the recipient of the IAPR-ICDAR Young Investigator Award in 2007. He was the general chair of the International Conference on Document Analysis and Recognition (ICDAR'2009) held in Barcelona in July 2009, and co-chair of the IAPR TC-10 Graphics Recognition Workshop of 2003 (Barcelona), 2005 (Hong Kong), 2007 (Curitiba) and 2009 (La Rochelle). Josep Lladós has also experience in technological transfer and in 2002 he created the company ICAR Vision Systems, a spin-off of the Computer Vision Center working on Document Image Analysis, after winning the entrepreneurs award from the Catalonia Government on business projects on Information Society Technologies in 2000.