Invariants extraction method applied in an omni-language old document navigating system

Quang Anh BUI, Muriel VISANI and Rémy MULLOT
Laboratory L3i, University of La Rochelle
La Rochelle, France
quang_anh.bui@univ-lr.fr, muriel.visani@univ-lr.fr, remy.mullot@univ-lr.fr

***Abstract*—We are currently working on the concept of an omni script and interactive word retrieval system for ancient document collection navigation, based on query composition. To make the query, user selects and composes writing pieces, which are invariant prototypes automatically extracted from the old document collection. In order to extract invariant prototypes from documents, invariants must be first extracted and clustered. Invariant extraction raises two main difficulties: detecting the ambiguity zones so as to extract primary strokes (writing pieces which do not contain any ambiguous zone) and grouping the primary strokes so as to form invariants. In this paper, we present existing methods for ambiguity zones detection and compare these methods on documents of different languages and periods to find out which one is more adapted in our context. Once ambiguity zones have been extracted, we apply our primary strokes grouping to obtain invariants and our clustering algorithm is applied over these invariants to find their representatives, (invariant prototypes). These invariant prototypes can further be used by the user to compose his/her query to retrieve words from the document collection.**

Keywords— word retrieval, stroke extraction, clustering, ambiguous zones detection

I. Introduction

A huge amount of human's knowledge is stored in ancient documents, spread in all over the world. Digitization is used to protect this heritage and to make it accessible to everyone. In order to provide fast access to that knowledge even though the masses of ancient documents available and their variability in terms of scripts and languages, different automatic transcription methods based on word recognition systems have been proposed. This process is an alternative to human transcription which is too slow and too expensive. However, the bad quality of old documents makes it difficult to achieve good results. Traditionally, most word recognition systems are specific to a given language. But, many ancient or rare languages and/or scripts do not have any dedicated word recognizer. "Word spotting" or "word retrieval" systems are an alternative to access historical document collections without any recognition system. "Word spotting" [2, 3] consists in locating all the occurrences of a given word image (query) that the user has previously selected in the document. The main drawback of this method is that user has to spot at least one occurrence of the word to search. To circumvent this problem, an alternative solution was proposed: "word retrieval" [1]. In "word retrieval", the user generates his query by using a predefined coding, where the code represents pieces of characters, pictograms, ideograms, etc. One drawback of most word retrieval systems is that it relies on a coding which is generally specific to a given script.

We are currently working on a generic omni-script and interactive word retrieval system dedicated to old documents. This system is based on 3 stages. The first stage (off-line) is the automatic extraction of invariant prototypes from a document collection. These invariant prototypes will constitute the codebook for the user to compose interactively queries in a second stage. The third stage consists in retrieving word images which are similar to the query. In this paper, we focus on the first step: invariant prototype extraction. The main objective of the first stage is to extract automatically consistent invariant prototypes from a given old document collection.

In order to extract invariant prototypes, we first extract invariants, also called in the literature "strokes". Strokes were defined as the path between pen-up and pen-down in the case of handwritten material, and are challenging to extract in the off-line case where no temporal information is available. As we consider old documents, we are working on an off-line system, with both handwritten and printed material. In our case, we therefore define "strokes" like a pattern which frequently occur within the document collection, this pattern consisting in a set of connected points of the writing between 2 ends or junctions. Even if many methods have been proposed in the literature [4, 5, 6, 7, 8, 9], stroke extraction from offline image remains an open issue. There are 2 main processes in a stroke extraction system: **ambiguity zone detection** (which consists in extracting primary strokes) and **primary stroke grouping** (which consists in solving the segmentation ambiguities by merging primary strokes to form invariants).

Our objective is then to extract, for each document collection, a limited set of invariant prototypes that may further be used for interactive query composition and word retrieval. Those invariant (stroke) prototypes must be in a limited number and meaningful to the user (because the user will use them to easily compose his/her query). We select them by clustering invariants, to find their representatives (invariant prototypes) that will be further used for the second step: query composition and the third step: word retrieval.

This paper is organized as follows. In section 2, we present some existing methods for ambiguity zone detection from offline documents and provide an experimental comparison of different stroke extraction methods using documents of different languages and periods. In section 3, we review existing methods for primary stroke grouping and propose a new method. In section 4, we present our invariant prototype extraction method based on the interactive clustering of invariants and we introduce our user interface for cluster visualization and interaction.

II. Ambiguity zones detection – primary stroke extraction

A. *State-of-the-art approaches*

There are parts of the writing where establishing which invariant it belongs to is not straightforward, e.g. crossings, touching components. These zones are called *ambiguous zones*. *Primary strokes* are defined as the set of connected points of the writing between 2 ends or ambiguous zones. Methods found in the literature for ambiguous zone detection are mostly based on the skeleton [7, 8, 9] or on the contour of the handwriting [4, 5, 6].

In [7], using skeleton of the image, the author find *candidate fork points* (CFP) which indicate ambiguous zones in the image, then, for each CFP, an ambiguous zone is located by a polygon whose vertices are contour points with the local minimum distance to this CFP. More generally, the advantage of skeleton based approaches is computational efficiency while maintaining acceptable geometric and topological attributes of the writing. But, results of the approaches are dependent on the stability of stroke width inside one document image.

In the case of contour based approaches, each point on the contour matches a position of the writing and it is a clue for ambiguous zone detection. In [4], authors demonstrated that ambiguous zones can be located using *dominant points* of the contour. These points correspond to stroke's end points, or to overlaps of consecutive strokes. In [6], authors classified ambiguous zones into 2 types (basic and complex) using dominant points. The main drawback of these approaches is that they rely on curvature estimation algorithms, which are mostly unreliable in the presence of degraded (old) documents. In [5], the authors detect ambiguous zones using a probabilistic model which is based on a parametric representation of strokes. The main drawback of this method is that its parameters must be tuned for any script or language.

Once ambiguous zones are detected and localized, "primary strokes" can be defined as the writing segments without ambiguous zones.

B. *Experimental comparison*

Ambiguous zones detection takes an important role in stroke extraction. In this section, we provide experiments over methods [7], [4] and [5], using our document database of different languages and periods.

Our database (see Fig. 1.) consists of 2 handwritten Latin pages (containing 2051 connected components) from the "Saint Gall" database (from the 9th century) [18], 2 pages (containing 934 connected components) from the old handwritten Chinese book "Bai shi wen ji" (written in 1618), and 2 pages (containing 1933 connected components) in printed Telugu (Indian) from the book "Bhavishya Puranam" (published in 1954).

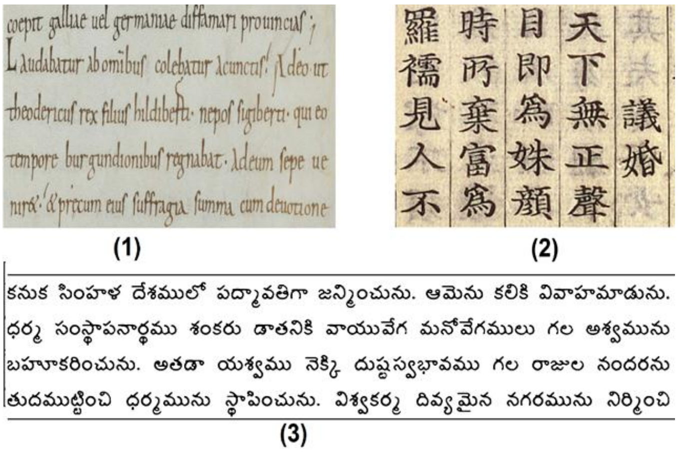


Fig. 1. Extract of: 1) Saint Gall database 2) Chinese database 3) Indian database

In each document, we first apply a pre-processing method to binarize the image and remove noise. Then, we extract connected components and detect ambiguous zones in these connected components using methods [7], [4] and [5]. To compare these methods, for each database, we apply each method using different parameters values, and then we manually annotate the image and count the number of missing ambiguous zones and the number of wrongly detected ambiguous zones, and finally we calculate precision and recall values. Table 1. shows the precision and recall values corresponding to each database and each method using the parameters for which each method gives the best result on the corresponding database)

	Method of Zhewen and Zhongsheng [7]		Method of Plamondon and Privitera [4]		Method of L'Homer [5]	
	Precision	Recall	Precision	Recall	Precision	Recall
Chinese database	0.9962	**0.9497**	0.8523	0.8264	**0.9973**	0.9217
Saint Gall database	0.9894	0.7356	0.8836	0.8971	**0.9918**	**0.9282**
Indian database	0.9980	**0.9613**	0.9743	0.9589	**0.9986**	0.9574

Table 1. Experimental results

As the method in [4] relies on an algorithm of curvature estimation, which is unreliable in the presence of degraded documents, it is the less efficient on our databases. This method performs the worst on the Chinese document, which is the most degraded, while it gives its best results on the Indian document, which is the newest and least degraded.

The method of L'Homer [5] provides the best precision results on our 3 databases (the method in [7] giving similar results though). This method uses a probabilistic model for representing strokes. For each database, we have to adapt the parameters of the probabilistic model to the type of script and the characteristics of the document. This requires a huge work and expertise while our goal tends to work with documents of different languages and non-expert users. Therefore, this method is not suitable for our system.

As we can see in Table 1, the method in [7] is very effective on the 3 databases of different languages, giving similar results to the method in [5] in terms of precision. Those good results may be explained by the fact that the contents of our documents are homogenous enough. Indeed, even in handwritten documents, the writer tends not to change stroke width in such old documents. The recall is generally better than with the methods in [4] and [5], except for the Saint Gall database, which might be explained by the fact that the handwriting is highly cursive in that case. Additionally, this method does not require any training stage so, different from the method in [5], does not have to be adapted manually to a given script/language.

Based on these experiments, we can conclude that the method in [7] is the best suitable for our word retrieval system.

III. Primary stroke grouping – Invariant extraction

A. State-of-the-art approaches

In this stage, primary strokes and ambiguous zones are grouped together in order to find out invariants.

In [7], the authors use a graph where each ambiguous zone or primary stroke corresponds to a vertex. If an ambiguous zone and a primary stroke are connected, then there is an edge between their corresponding vertices. The authors use continuity analysis to determine whether 2 primary strokes joined with the same ambiguous zone can be merged or not. Continuity analysis is based on a Bayesian classifier, using features (such as *angle deviation*, *width difference*, *curvature variation*, *etc.*) extracted from 2 primary strokes joined with the same ambiguous zone, and based on an algorithm for searching all the simple paths in the graph satisfying a certain number of conditions: *end constraint, non-end constraint, smoothest criterion and Y-junction criterion* [7]. Because of the use of a supervised classifier, this method requires a preliminary training step on manually annotated samples of the document collection, which is not possible in our case where we have no *a priori* information about the language/script.

In [4], the authors use a general decision function to determine whether 2 neighboring primary strokes have to be grouped or not, instead of using a supervised classifier. This method can be used in the general case. But, designing and parameterizing such a general decision function is hardly tractable.

In [5], the authors have a statistical analysis of the NIST database [15] and note that the percentage of ambiguous zones connected to more than 4 primary strokes is very low. Based on this analysis, the authors limit their algorithm to deal with ambiguous zones connected to less than 5 branches. Then, they can list all possible configurations (topologies) for an ambiguous zone. This method uses *a priori* knowledge for a specific database, so it cannot be used in our case.

B. Our proposed invariant extraction technique

Our objective is to merge the primary strokes extracted using the method in [7] so as to obtain our invariants. Similar to [7], we represent primary strokes and ambiguous zones using a graph. Each ambiguous zone and primary stroke corresponds to a vertex. If an ambiguous zone and a primary stroke are connected, then there is an edge between their corresponding vertices. But, we cannot rely on a supervised classifier to group primary strokes like in [7] because our goal tends to work with documents of different languages and with non-expert users; we prefer to use a decision function. This function is based on Gestalt parameters [17] that are involved in the human visual processing of writings. These parameters are: 1) the section of the stroke (strokes generally have sections of approximately the same width, especially in old documents) and 2) the good continuation rule (the curvature of the stroke cannot abruptly change). To determine if 2 primary strokes S_i and S_j joined by an ambiguous zone S_a should be grouped or not, we use a process in 2 steps:

Firstly, we estimate the average widths w_i and w_j for each primary stroke. The measure $w_{ij} = |w_i - w_j|$ describes the width difference between S_i and S_j. Based on the first Gestalt parameter, if w_{ij} exceed a given threshold, the pair of primary strokes (S_i, S_j) cannot be grouped and therefore belong to 2 different invariants.

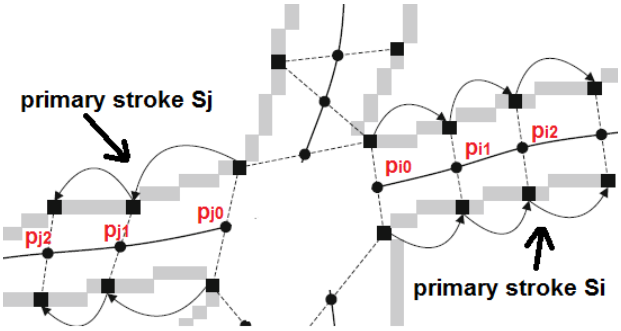


Fig. 2. Sample points of writing trajectories (SPWT) of 2 strokes [4]

Secondly, Sample Points of Writing Trajectories (SPWT) are extracted from each writing segment using the algorithm described in [4] (see Fig. 2.). Let us denote $S_{q_i} = (p_{i0}, p_{i1}, \dots, p_{im})$ the sequences of a SPWT corresponding to a given primary stroke S_i, joined with an ambiguous zone S_a. We define the *support chain* $(p_{i0}, p_{i1}, \dots, p_{ig_i^*})$, $g_i^* \geq 3$ as the subsequence of S_{q_i} starting from p_{i0} (the point being the nearest to S_a) for which the direction of the path from p_{i0} to $p_{ig_i^*}$ remains stable on the whole path. More formally, let us denote V_{g_i} the first principal component (*i.e.* the main direction) obtained by applying Principal Component Analysis on the set of points $(p_{i0}, p_{i1}, \dots, p_{ig_i})$. We define g_i^* as the index of the last point in the sequence so that the angle between $V_{g_i - 1}$ and V_{g_i} remains inferior to a predefined threshold ϕ_{thr}

For each ambiguous zone S_a, given 2 primary strokes S_i and S_j joined with S_a, we then define 2 variables: the angle deviation $\theta_{ij} = angle(V_{g_i^*}, V_{g_j^*})$ and the curvature deviation γ_{ij} (calculated as in [7]). Based on the second Gestalt parameter, the primary strokes (S_i, S_j) for which γ_{ij} is minimum are grouped if and only if $\theta_{ij} < \theta$ (where θ is a fixed threshold)

IV. Invariant Prototypes Extraction

A. *Invariant clustering*

Once all invariants in a document collection have been extracted, we then apply a clustering algorithm to group strokes into clusters of similar shape and select the cluster prototypes. These prototypes will be further used by the user to compose interactively his/her query. They are computed based on a description of the invariants relying on a set of well-chosen features.

Invariant description: Because of our applicative context, the features used for describing the strokes as the input of the clustering should not be rotation invariant (otherwise, in Latin, the letter "n" could be clustered with the letter "u" for instance). Because of the homogeneity of the contents of the ancient documents, the features do not have to be scale invariant (otherwise, the letter "i" could be mixed with the letter "l" for instance). The set of features that we compute for each stroke image is composed of:

1) Elongation [14]: Ratio of the height to the width of the shape's minimal bounding box.

2) Solidity [14]: Ratio of the area of the shape to the convex hull area of the shape. Solidity describes the extent to which the shape is convex or concave.

3) Rectangularity [14]: Ratio of the area of the shape to the area of the minimum bounding rectangle. Rectangularity represents how rectangular a shape is.

4) Circularity ratio [14]: Ratio of the area of the shape to the area of a circle having the same perimeter. Circularity ratio represents how a shape is similar to a circle

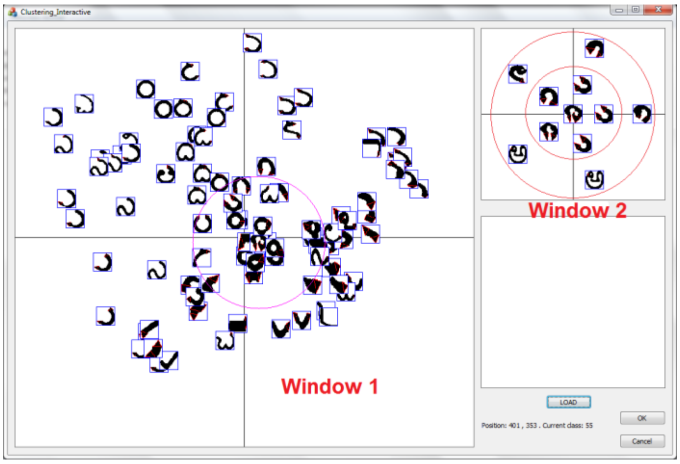
5) Bounding box [16]: Bounding box method approximates the shape of the invariant using a fixed number of rectangles of varying size and computes a vector of features representing the shape of the obtained lattice of rectangles. Normally, bounding box method uses a normalization method to make the features invariant to rotation. But in our case, we do not apply this normalization because the features do not have to be rotation invariant.

Invariant prototype extraction: First, a pre-clustering is performed by applying the BIRCH clustering algorithm [13] using the set of simple features: 1,2,3,4. We choose the BIRCH algorithm because it is fast, hierarchical and is proven to be efficient for image clustering [11]. We choose features 1, 2, 3, 4 for pre-clustering as they are simple features that we can use as filters. Second, for each pre-cluster, re-clustering is applied by using several sequential clustering phases [10] and the feature 5. Feature 5 is used in the second step only to refine clustering results obtained from the first step. We do not include it in the first step, as it is scale invariant and we do not wish to get scale-invariant clusters. The sequential clustering phase provides a variable number of clusters. Final clusters are defined as the groups of strokes that are always clustered together, enabling us to filter outliers.

For each stroke, we calculate its Silhouette Width (SW) score [12]. Then, for each cluster, we define the corresponding invariant prototype as the invariant which has the highest SW score.

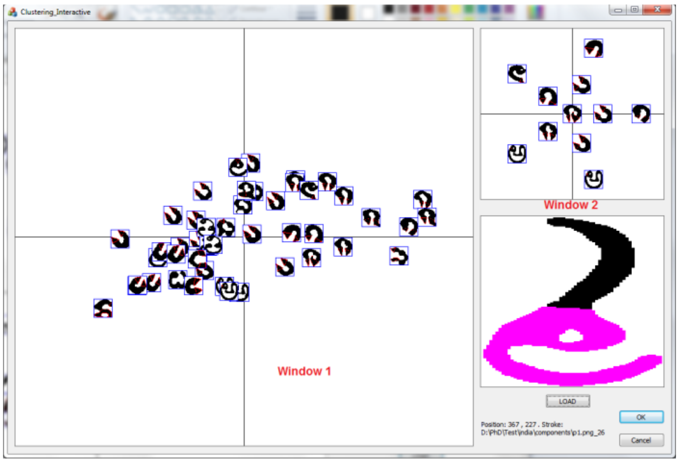
B. *Cluster visualization*

After the clustering invariants and finding prototypes, we build a graphical user interface to visualize invariants and invariants prototypes. Figures 3 and 5 present our interface showing invariant prototypes for the Indian and Saint Gall databases.



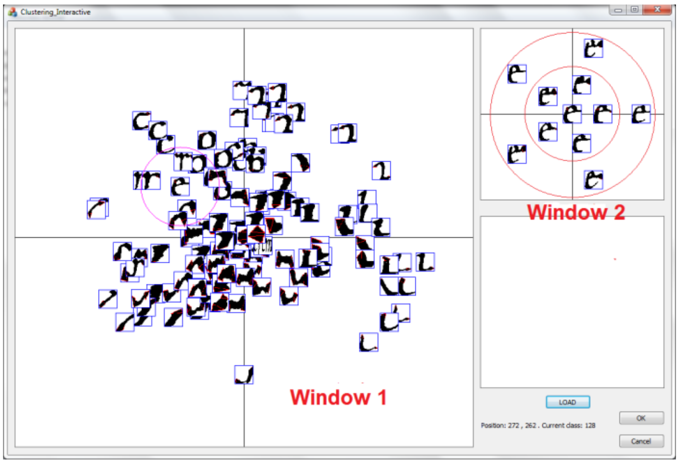
Position: 401 , 353 . Current class: 55

Fig. 3. Invariant prototypes of our Indian database



Position: 367 , 227 . Stroke:
D:\PhD\Test\india\components\p1.png_26

Fig. 4. Details of a cluster



Position: 272 , 262 . Current class: 128

Fig. 5. Invariant prototypes of our Saint Gall database

All invariants prototypes are displayed in window 1, in a plane composed of the two first principal components extracted from their feature vectors. When the user moves his/her mouse over a prototype, a red circle is displayed around the prototype, which indicates the radius of the cluster in the feature space. In window 2, this prototypes is displayed at the center of the window, and the closest invariants to the prototype are displayed at the inner ring while the invariants farthest to the prototype are displayed in the outer ring. If the user double-clicks at a prototype, window 1 displays all invariants of this cluster (Figure 4).

This interface allows the user visualize the invariants and analyze the clusters. We are currently working on integrating an interaction/personalization module which lets the user interact with the system so as to create the invariant prototypes he's more comfortable with for query composition.

V. CONCLUSION

In this paper, we introduce our invariant extraction method used in our omni-language word retrieval system. There are 2 main processes in an invariant extraction system: **ambiguity zone detection** and **primary stroke grouping**. We compare existing ambiguous zone detection methods on 3 data sets of different languages and find out that method in [7] is the most suitable in our context. This method gives good result even in degraded document and does not require any training stage, and therefore can be used for any script. We introduce our primary stroke grouping method, using a general decision function to determine whether 2 primary strokes joined with the same ambiguous zone can be merged or not, based on parameters that involved in the human visual processing of writings.

One of our problems is that some results of our invariant extraction method are different from human's conception. It means that some invariants are not meaningful enough to the user to compose his/her query in the composition step. In the future, we will do researches to overcome this problem, such as the idea of *interactive primary stroke grouping*.

After invariant extraction, we then apply our clustering method to find invariant's prototypes that will be further used for the second step: query composition and the third step: word retrieval. An interface is built, allows the user visualize the invariant and analyze the clusters. As our invariant prototypes must be meaningful enough for the user, using this user interface, we will build the *interactive clustering* module which lets user provide feedback to improve the clustering result.

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