# Handwriting similarities as features for the characterization of writer's style invariants and image compression

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**Abstract.** In this paper, we propose a new approach of similarity retrieval in ancient handwritten documents. Similarities are retrieved on shape fragments which can be analysed according to different granularities (from the grapheme to the character size) depending on the handwriting quality, regularity and sharpness. The approach is based on a "segmentation free" methodology which considers the image with all frequencies and Gray levels. The method has been applied for two purposes: to establish the basis of a new handwritings compression approach based on handwritten images specificities and to show that only shape fragments can efficiently be used for writer characterization. We present here the global methodology for the similarities characterization which lies on an oriented handwriting shapes decomposition. First results for data compression and writer characterization are very encouraging in a field where there is no anterior work.

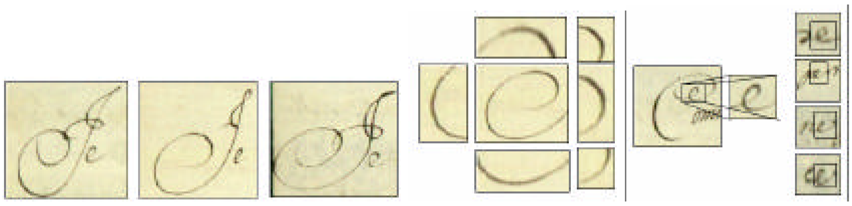
**Keywords:** Compression, writer's style characterization, Gabor featuring, Deriche outline detector, similarities retrieval.

## 1 Introduction

The digitalization of the patrimonial scientific and cultural documents facilitates the access to a larger audience and offers new services like the online consultation of rare documents, the fast and economic duplication of works, a quick information retrieval and the possibility of knowledge sharing with other readers, [18], [8], [6], [13]. We can also notice that digitized documents cause difficulties in terms of storage and transmission on a flow-limited network. Those needs and remarks are at the basis of an innovating digitalization project called ACI MADONNE[1] and our contribution is presented here. From there, we prove the needs to develop compression and information retrieval methods that are well adapted to images content. They generally require new data format definitions for remote contents inquiries. In that context, we can easily show that the images compression became a necessity. Only lossy compression with an acceptable perceptible loss of information may reduce the weights of images. Only users can really evaluate the fidelity of broadcasted images compared to the originals, the acceptable loss of information and the speed of access through the network. The existing compression formats like JPEG, DJVU and DEBORA are unfortunately not effective on handwritten documents images, [6]. The limitations of these methods lie on the great complexity of the features present in the handwritten texts and on the difficulty to localize precisely handwritten parts of the page. Indeed, we can notice that a robust handwritten documents segmentation algorithm and shape recognition need at least shapes redundancy, noticeable relevant similarity and some handwritten regularities which can not easily be retrieved in degraded and noisy images corpus. The location of redundancies and is not limited to the characters but can be extended to any part of the image which presents distributed similarities, see Fig. 1.
In that context, it is necessary to develop specific methods to precisely localize handwritten text areas and redundant shapes without any segmentation, [21]. Existing approaches of regular handwritten text and drawing location (connected components analysis, directional and

[1] ACI MADONNE - ACI Masse de données of the pluridisciplinary thematic network, RTP-Doc, 2003-2006.

morphological filtering, simple directional projections, [12]) are inefficient in noisy and variable documents.



1.1 1.2 1.3

**Fig. 1.** Shape granularity. **1.1.** Macroscopic similarity. **1.2.** Graphemes based decomposition. **1.3** Graphical delocalized shape similarities.

The handwritten documents on which we have conducted our work show all those specificities: difficulties of line and word segmentation, natural (or usage) degradation, imprecision and irregularities of drawings. This paper presents a new segmentation free approach and characterization of partial similarities in ancient handwritten documents. The method has been developed to improve usual handwritings compression approaches that are not adapted to patrimonial images specificities. What is more, the similarity retrieval can be applied to distinguish a writing style to another and has shown to be a promising tool for writer identification.

# 2 General principle of the approach

The shapes which are required for the similarities retrieval are not necessarily words or letters but they can simply be constituted of small loops of letters (graphemes) which can be localized at different places in the manuscript with possibilities of scale change, rotation and translation. The grapheme is considered here as a stable graphical unit for a same writer and is composed in a continuous pen motion. The similarities are defined in regard with our compression and characterization objective: it is not because two words are the same that they present a real similarity, see Fig. 1.

Our proposition consists in characterizing the grey level shapes by a fragmentation of the handwriting and a detection of oriented segments. The location of the oriented patterns is based on the exploitation of Gabor banks filters and specific Deriche based outlines descriptors. These tools enable us to show handwriting line segments with identical orientations and precise points in the contours which present a change in orientations. We produce a partitioning of the line zones in variable sized portions which are signed by features vectors based on their main orientations. The similarities retrieval has been conceived to be robust to scale changes, to rotations and of course to translations.

# 3 Handwriting segmentation in degraded environment

In this part we present the basis of our approach for handwriting grey level image segmentation into oriented line segments. The implementation of a parameterized Gabor filters bank is based on a decomposition of the frequential domain of the documents image and is achieved so as to localise all oriented segments in the writing.

## 3.1 Frequential analysis by Gabor filters

The principle consists in breaking up the original image into directional maps, using Gabor filters with an adequate parameter setting based on the most significant directions of the image. These directions are initially evaluated from the image spectrum. We used here the multi-channel filtering technique to localize precisely directional information of handwritten data. This approach is inspired by the multi-channel filtering theory for processing visual information in the early stages of the human visual system, [19]. Those filters are able to suppress low frequencies patterns by underlying handwriting text lines with a precise selection of parameters for frequency, orientation and bandwidth. The selection is highly dependent on the image. But this automatic parameterization is generally a non trivial process in image analysis because it needs to parameterize the filters in each selected direction ?, [5]. The accurate implementation of a complete Gabor expansion entails a generally impractical number of filters. In our work, we propose an automatic process of bank filters selection, [19], [10]. The Gabor function is defined as a Gaussian function modulated by a sinusoidal wave (expression (1)).

$$G(x, y) = \frac{1}{2ps_x s_y} e^{-\frac{x2}{2s_x^2}+\frac{y2}{2s_y^2}} e^{j2p(xf_{x0}+yf_{y0})} \qquad (\mathbf{1})$$

The filters bank is based on the partition of the frequencial domain into differents channels, each being characterised by angular sector corresponding to four chosen directions (N=4, ?=0°, 45°,90°,135°): in our study, we have limited the number of filters by selecting relevant directions. s x and $s_y$ are respectively the x and y, width of the Gaussian function; $f_{x0}$ and $f_{y0}$ are the modulation special frequencies. This filter is an oriented pass-band type filter with a complex impulsional response: low frequencies (in homogeneous regions of the image) are situated at the center of the Fourier Transform and the high frequencies (in the frontiers of handwritten lines) are located at the edges, see Fig. 2.

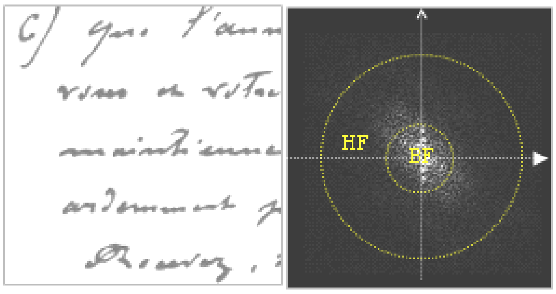



**Fig. 2.** Spectral representation of a document image in high and low frequencies.

More the filtered areas are close to the FFT center (in the low frequencies domain), more the background of the image is filtered. Inversely, when high frequencies are weakly attenuated, outlines of handwriting regions are highly underlined. The Gabor filters have been tuned so as to remove low frequency background shapes and to enhance text lines, by privileging selected oriented high frequencies present on the shape contours. In this way, the adjustment of the parameters $f_0$ and s is determinant to localise in a precise manner the high frequencies. These two parameters have a particular influence on the results of the oriented contours segmentation. They are fixed for an entire book of a same author (same support and same ink properties). This parameterization is automatically computed and inspired by the Pratt optimisation method, [14]. The two filters parameters (central frequency $f_0$, width s) are initially chosen experimentally for an entire book (or a set of digitized images from a same collection). The optimisation of these parameters choice depends on the evaluation of the contours segmentation for each value of $f_0$ and S. The evaluation is based on the closing of contours, the precision of location just in the frontiers of handwriting shapes and the thickness.

### 3.2 Directional maps

This image is then divided into four directional maps each containing a set of oriented segments in the same direction. Fig. 3. summarises the separation into four directional plans in an initial image which has been extracted from the handwritten corpus of l'Ecole des chartes, [7]. The combination of the four different directional maps allows to reconstruct with a great precision the entire high frequency handwriting. It illustrates with a great precision the contour of the writing and allows in that sense to consider the only four directions (?=0°, 45°, 90°, 135°). The reconstruction of the Fig. 4. is the result of three logic AND operations between the four maps.

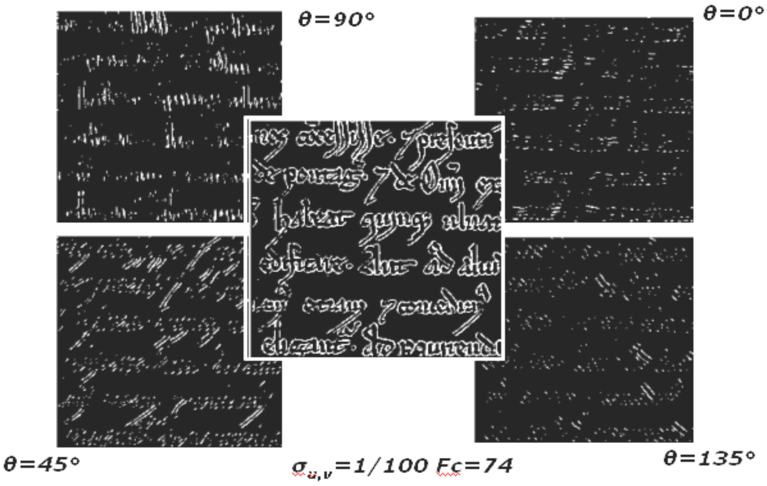
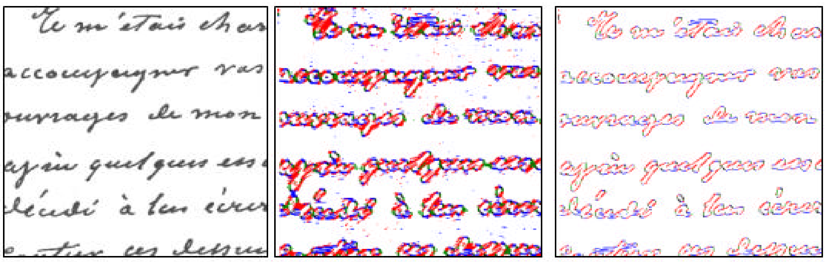



**Fig. 3.** Contours maps reconstruction of a text image from four directional maps.

After the reconstruction of the final contours maps from the four Gabor directional maps, we have notices that the contours could not be unitary (only one pixel thickness). Therefore, the object of the next step is to reduce the width of these contours to only one pixel in order to facilitate their analyses and coding. For this, we suppress all non maximal Gabor responses. The principle has been inspired by [4] and [11]: in the orthogonal direction to contour direction, we only keep the maximal points amplitudes. In practice, it is necessary to make sure that only one response is detected. Only local maxima in the direction orthogonal to the contours direction are therefore conserved (see Fig. 4.).

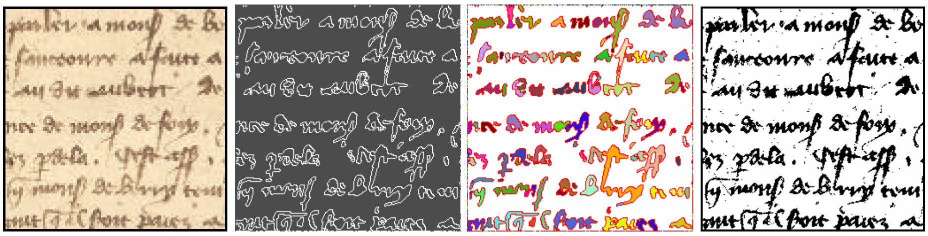


4.1 4.2 4.3

**Fig. 4. 4.1** Original image, **4.2** contours maps with overall Gabor responses, 4**.3** contours map reconstruction with maximal responses processing (Sb=10 and sh=10).

### 3.3 Connected shapes decomposition

Starting from the shapes decomposition into oriented contours, we must be able to associate an oriented segment with its original shape. Segments can be limited to simple graphemes (small isolated segments) or on the contrary extended over many letters to form a word. Therefore, the notion of handwritten *entity* is very large. The association of contour and shape is achieved by a segmentation process into connected region. This step provides the image partitioning into zones of interest. The analysis of topological relation ships between pixels leads to the aggregation of connected shapes. This process is realized without any thresholding step, see Fig. 5.



5.1 5.2 5.3 5.4

**Fig. 5. 5.1.** Original image. **5.2.** Deriche frontiers extraction. **5.3.** Shape extraction by cooperation between Deriche outliner and regions growing. **5.4.** Illustration of a non-satisfying Niblack thresholding version.

The method used the *Deriche* contours detection which guarantees a good precision and fast segmentation. It is followed by a regions *growing* process starting from an internal germ to element in the grey level image and guided by the Deriche contours map. By associating shape frontiers, and shape content, we obtain a very realistic representation of handwriting that even an optimized thresholding process is not able to highlight. Our motivation to develop this cooperation is related to the necessity to consider both the contours of shapes and their content which preserve information on orientation and curvature (in the contours) and thickness of the writers' nib.

## 4 Hierarchical approach for oriented shapes signature

The map of Gabor directional contours contains a lot of information which characterize a form or a group of graphemes. In this part, we define a relevant and robust to simple transformations signature of oriented segments (the shapes). Within a scale change, a rotation and a translation, two similar shapes with different sizes have to look alike. This signature will be used to find all similar shapes over an entire page area from a same writer and over an entire book even different writers are implicated. In practice, we have developed a succession of steps by defining three signatures levels with a hierarchical point of view of shape structures: from the coarsest (Directional Rose Signature SDR) to the finest (Histogram of Projected Directions Signature SHPR and Junction Points Signature SPJ), see Fig. 6.

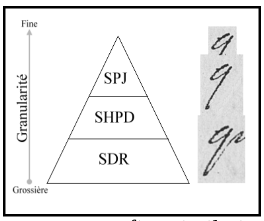



**Fig. 6.** From coarse to fine similarity retrieval.

The performance of each type of signature is related to its capacity to increase the similarity between perceptibly similar shapes so as to minimise *residual* differences between a reference shapes and all of them similar in a context of compression. It must be reminded here that in handwriting dedicated compression scheme the *residues* constitute all differences between the shapes chosen as references for the image coding and the substituted shapes at the time of coding. Theses differences constitute the compensation plan which re-establishes when necessary the differences between the reconstructed image and the original image. For that purpose, we propose a hierarchical approach of signature coding starting from the most global shapes properties with the quantification of orientation distribution of shapes contours, to finest structural properties of shapes based on the location and the succession of all *junction points* between oriented segments. This hierarchical initiative of similarity retrieval allows to process even highly noised images with irregular and instable writing styles. The principle of shape analysis lies on the scan of the page image with a mobile variable sized window which computes distances between a signed reference shape and all patterns present in the window. Currently, the size of the reference motif can be either automatically chosen or manually at any place in the text. Here are presented the hierarchical similarity measures and the principle of distances computation.

### 4.1 Direction rose and invariance to the scale (SDR)

In this approach we present a new signature based on the normalized number Nap($?_i$) of occurrences of contours points for all $?_i$ directions (0°, 45°, 90° or 135° ). This number is given by the following expression (2):

$$N_{ap}(q_d) = \frac{1}{N} Card\left\{C_{q_d}(x,y) \middle| P(x,y) \in Cntours\right\} \tag{2}$$

*$?_i$* is the direction of a contour point *P(x,y)*, *$C_{?i}$ (x,y)* is the number of contour points for the *$?_i$* direction, N is the total number of contour points in the analysis windows including the motif to be studied. The resulting directional occurrences in the analysed shape are given by the expression:

$$N_{ap}(S_f) = \left\{N_{ap}(0°), N_{ap}(45°), N_{ap}(90°), N_{ap}(135°)\right\}$$

The *similarity* between the two shapes $S_f$ and $S_{ref}$ is estimated with the Euclidean distance between the two sets Nap($S_f$) and Nap($S_{ref}$)in expression (3):

$$D(N_{apS_f}, N_{apS_{ref}}) = \sqrt{\sum_{i=\{0°,45°,90°,135°\}} (N_{apS_f}(q_i) - N_{apS_{ref}}(q_i))^2} \tag{3}$$

This estimation of the local densities of oriented contours points for each shape is explicit by the construction of a *direction rose*, see Fig. 7.

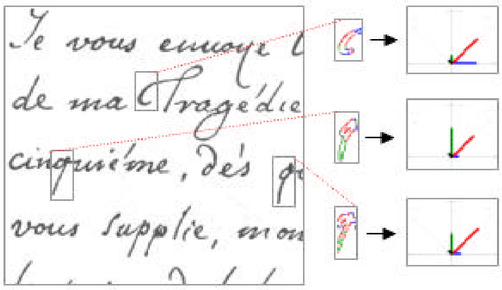



**Fig. 7.** Direction rose between similar shapes and presence of an intrusive pattern.

For a given shape, the rose gives the result of the quantification of each direction. It will be used to find two like looking shapes at different scales, with invariant ratio of oriented segments. This property confers to the measure significant robustness to size changes which are very frequent in handwritten texts, see Fig. 8. It also permits to easily disregard shapes which do not contain same direction ratios: we can consider that they do not present any degree of similarity. This approach can only be used for an only coarse shapes separation: two shapes can have a similar rose and a totally different structural composition. Complete results are presented in the next *experimental* section. For this reason, this approach must be refined with a structural approach based on the analysis of the directions histograms which highlight spatial localisation of each direction.

### 4.2 Histogram of projected oriented segments (SHPD)

The first refinement is based on a structural approach which lies on the histogram of projected oriented segments. Two shapes (which have been selected from the previous SDR step) are considered as similar in the SHPD approach, if their histograms of projected oriented segments look similar. The quantification of this similarity is given by the computation of the correlation coefficient between each histograms of a same direction. The coefficient of correlation between two histograms vectors $H_i$, $H_{iref}$ is given by the normalised product:

$$CoefCor(Hi, Hiref) = \frac{Hi \cdot Hiref}{\|Hi\| \cdot \|Hiref\|}, \quad \text{with} \quad \|H\| = \sqrt{\sum_{K=0}^{N-1} h^2(k)} \qquad (4)$$

The coefficient $C_{oef}\,_{Cor}(H_i, H_{iref})$ is included between 0 and 1 and is maximal for $H_i = H_{iref}$. The more the difference between $H_i$ and $H_{iref}$ is important, the more $C_{oef}\,_{Cor}(H_i, H_{iref})$ is small finally. The similarity value is estimated by the $S_{im}$ expression:

$$S_{im} = \sum_{i=\{0°, 45°, 90°, 135°\}} P(i) \cdot C_{oef}\,_{Cor}(H_i, H_{iref}) \qquad (5)$$

A threshold $S$ fixes the degree of similarity between two shapes. It can be automatically chosen for all motifs of a page. The higher $S_{im}$ is (greater than $S$) the more we consider that two shapes $M_i$ and $M_{iref}$ are similar.

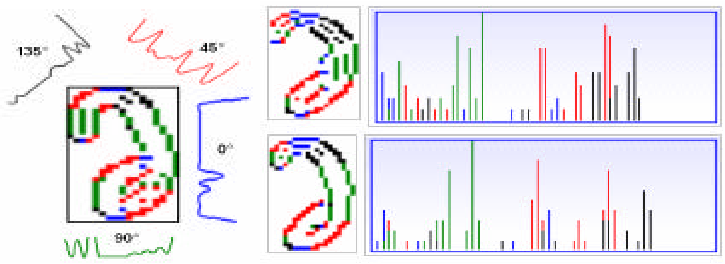



**Fig. 8**. Example of two projected histograms for two similar motifs with a coefficient of correlation = 0,55.

### 4.3 Junction points structure (SPJ)

The last refinement is based on the definition of a structural signature composed by the list of junction points at the limits of each oriented segments. The calculation of the signature is based on the resulting list of all direction change points between two oriented segments. It is based on a progression going from top to bottom and from left to right with a single scanning of the map of the labelled contour points. Fig. 9. shows an example of motif and the succession of junction points at the limits of direction changes. To simplify the calculation, we only have considered the possibility for a junction point to separate two directions (no intersection between three directions). All of the junction points j(x,y) are coded by three values: their position in the list, the current direction and the next direction according to the definition of contour points.
Let's consider $S_f(i)$ a first shape junction points signature and $S_{ref}(i)$ a reference shape signature, with i = 0…N and N the total junctions points number. The Hamming distance has been chosen to quantify the differences between $S_f$, $S_{ref}$. With a Hamming distance given by:

$$D(S_f, S_{ref}) = \left\{ Card \ \left\{ i \in [1, N] \ \middle| \ S_f(i) = S_{ref}(i) \right\} \right\}$$

We can define the similarity between $S_f$ and $S_{ref}$ by : $P_s(S_f, S_{ref}) = 100 \cdot \frac{N - D(S_f, S_{ref})}{N}$ (6)

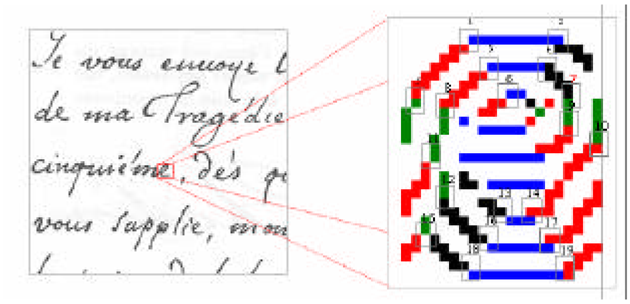


**Fig. 9.** Junction points of an isolated motif

We consider that two shapes are similar if the ratio $P_s(P_f, P_{ref})$satisfies a predetermined threshold. It is recommended to fix this threshold for a same book of a same author.
From the SDR approach to the finest SPJ, we extract similarities refined at each step. The similarity retrieval can not be evaluated in terms of correct retrieval (according to a precision recall principle) because the objective here is not exhaustive similarities retrieval but it corresponds to the extraction of real visually similar patterns. The evaluation must be realized through an objective of compression with the computation of the differences between the reference shapes and all retrieved similarities (the residues map). The best matching are obtained by successively applying the three methods. Let's see now how to evaluate this methodology on ancient document for two targeted applications: regular handwriting compression and writers identification.

# 5 Experimentation and discussion

## 5.1 Comparative discussion of the three approaches

To validate our approach, we have chosen to sort 130 shapes from a same image in comparison with a reference shape "a ", see Fig. 10.

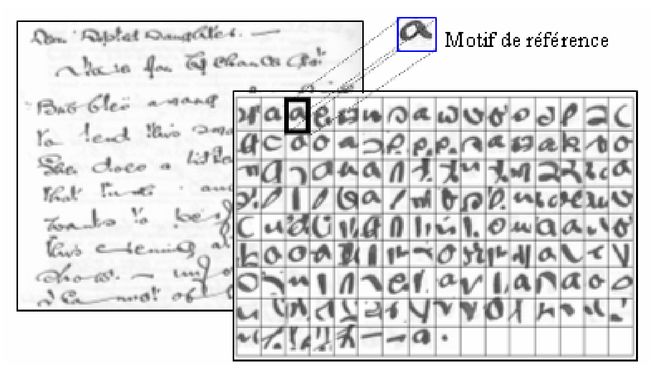
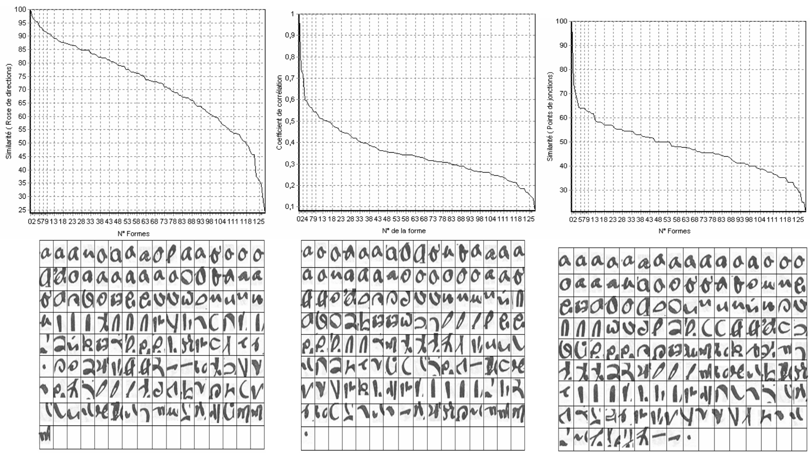



**Fig. 10.** Original image and a base of 130 motifs here randomly arranged.

The objective here is to evaluate each approach independently and to quantify their ability to sort the motifs in decreasing order of similarities. The protocol which has been adapted from [13] consists in comparing each motif to the referential shape for each of the three methods previously explained (Similarity by direction roses ((SDR)), similarity by correlation of directional projection histograms ((SHPD)), and similarity by junction points coding ((SPJ)). The variation of each similarity measure (obtained by for each method) is individually quantified in Fig. 11.



11.1 11.2 11.3

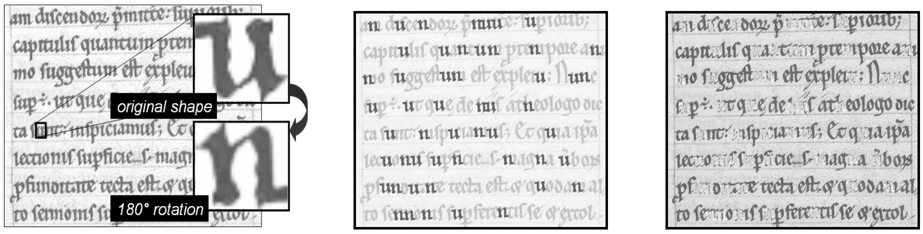
**Fig. 11. 11.1.** Variation of similarities (with the SDR method). **11.2.** With the SHPD method. **11.3.** With the SPJ method.

We can notice on the curve slants in Fig. 11. that the more precise the method is (the SPJ and SHPD methods derive from a finer analysis (structure) of the shapes), the better the similarities are revealed and the differences between shapes increase. This phenomenon can be explained by the fact that a high precision in the description of the structure of the motifs reduces the global similarity between shapes. We can explain this phenomenon by the fact that great accuracy for the pattern structure description can decrease the chances of matching because of a lower similarity. These three approaches can be combined in a hierarchical use of the patterns : from the coarsest one ( SDR) which will be use at first, to the finest (SPJ). The first approach gives a global similarity measure, the second one can be more precise, using structure extraction. On the examples we give here, the application of directional roses gives more than 96% of correct matching of similar patterns. To obtain a more accurate matching, we have to combine these three approaches in a hierarchical way. This combination is in test at the moment.
Most of the existing matching methods use a fixed and linear protocol. A “relevance feed back” step is not possible [2], [16]. Mixing our three methods allows to change the classification of similarities, by taking into account inter-classification and by deleting the patterns that do not succeed to a finer analysis (SHPD or SPJ). We will focus now on how we can compute a similarity measure on whole documents using pattern research.

### 5.2 Application to regular similarities retrieval on middle-age manuscripts

Our approach does not lie on a classification of connected shapes overall the page area but on shapes which can have variable size and which can be or not included in connected components (inside words for example). This property allows retrieving hidden similarities inside connected patterns without being limited to an analysis guided by the size of patterns. In Fig. 12. we have chosen to illustrate the result of similarity retrieval on a regular middle-age manuscript from a manually selected shape “*u*”. The similar patterns have been selected with the SPJ method. The robustness of the SPJ method to rotation has been applied in the sample. Both “*u*” and “*n*” can be indifferently selected in the image. The most similar patterns (satisfying a similarity *threshold* of

70% of the SPJ method) are marked in dark grey in Fig. 12.2. The map of residues (12.3) illustrates the difference between the original image and the resulting substituted image.




**12.1** **12.2.** **12.3.**

**Fig. 12. 12.1** Original regular medieval manuscript and reference shapes "u" and its rotated "n". **12.2** Result of the similarity retrieval. **12.3** Residues map.

The evaluation of the retrieval is more difficult to realize on images of old manuscript because of the presence of noise, and the irregularity of the features. On the paleographic images of middle Ages, results are very stable and very redundant features give very high results of similarities. On the previous example, a single shape covers more than 30% of the total surface of the handwriting area. The analysis on a large scale (on a complete corpus) led us to observe that the choice of the shape granularity was determining.
The analysis on a large scale (on a complete corpus) led us to observe that the choice of the shape granularity was determining. Indeed, a too large pattern (coming from a whole word for example) can have just one or two (at most) occurrences in a single page. The redundancy rate of this research becomes thus considerably reduced and consequently, the compression coding becomes strongly less efficient. Simultaneously, too small patterns are repeated very frequently on the page but the surface occupied by these copies will not lead to an exploitable and effective segmentation for compression. In such situations, it is necessary to encode a great number of segments and to increase the dictionary of similar reference patterns. This choice of reference patterns (not currently automated) is a very important part of the compression process. This automation is currently in development on our palaeographic database of 500 pictures.

### 5.3 Application to writing invariants retrieval

The similarity retrieval has been applied here to detect invariant similarities on author manuscripts with an objective of writing authentication and identification. The principle lies on a manual extraction of most significant shape invariants, (see Fig.13.) Here, we have voluntary chosen the Montequieu's corpus which is characterized by the great shapes irregularities. The great variability of shapes in the handwritten text has constrained us to choose lower similarity thresholds guaranteeing a greater tolerance of results. In this figure two recurrent shapes have been retrieved and classified according to their similarity with the only SDR method. Refinement can be realized to extract more fine similarity with a precision which is illustrated on Fig. 6. Similarity rate depends on chosen granularity.
It has been shown that the detection of invariant shapes is an effective way to characterize a writer and to authenticate a manuscript, [17]. The choice of the signature method depends on the granularity of the patterns that represent a writer (see Fig. 6.). The choice of the granularity must be given to experts in paleography and human sciences, who are the most able to choose the better set of patterns to represent efficiently a writer. This set of patterns can be established from a single page or from several pages from the same book or even from different books on an entire collection. In the following step, we compute similarities between patterns of a single page (see Fig.13.) and we generalize the similarities retrieval by analyzing all possible shapes of other pages of the same writer and other pages from another writer, (see Fig.14).

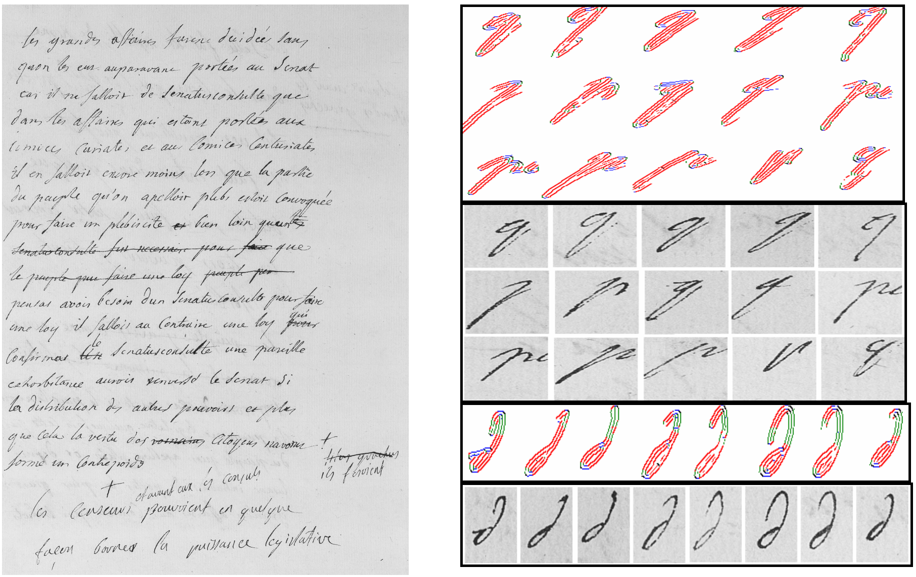


**Fig. 13.** Original manuscripts from Montesquieu (1750). Characterization (with oriented segments) and sorting of invariants according to their similarity to a reference.

The choice of invariant patterns allows to realize a first diagnostic between pages so as to answer to the following question: “Does a designed writer write a request page?” In Fig. 14., the SDR method shows its ability to retrieve complete pages of a same author while isolating other pages which do not content any similar shapes. With an unique shape « *q* », we can observe that the SDR approach is a good separator between writers. In practice it is inefficient to use a single motif to compare different writers. This study is currently generalized with a comp lete list of significant shapes (the box of…) for each writer so as to realize a complete identification of Montesquieu’s secretaries all along his piece.

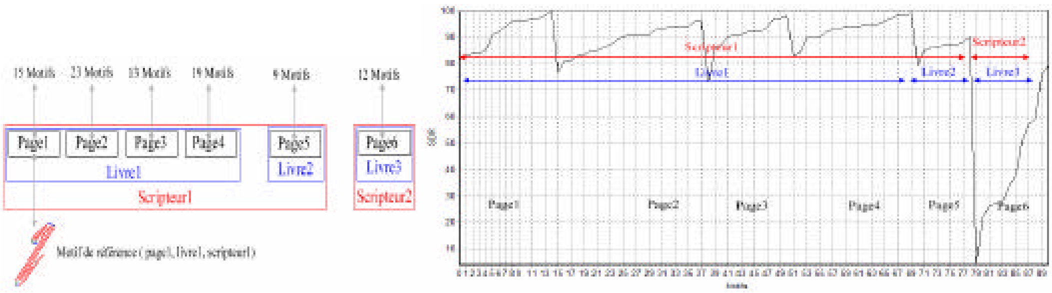



**Fig. 14.** Single motif retrieval in a sample of Montesquieu corpus. Illustration of the ability of a SDF approach to discriminate two writers.

## 6 Conclusion

Handwritten shapes are very difficult to model: this phenomenon is due to shapes irregularities and ancient patrimonial manuscripts degradations. Even for a same writer, we can sometimes find inner variabilities in a same book. By taking into account the possibility of a writing to present shapes irregularities, we have presented here a novel contribution for *thresholding* free approach of handwriting characterization and compression. We have presented here the step of similarities retrieval which decomposes the original complete signal into directional maps. Those maps contain size variant shapes that are retrieved over the entire page area. Technically, we propose original tools for handwriting location and characterization by using a Gabor based directional featuring and a complete graphemes signature. The signature is used to retrieve similarities with three complementary approaches which are robust to rotation (SDR, SHPD), scale (SDR, SHPD) and translation (SDR, SHPD and SPJ). As for now, the method is very effective on handwriting documents where graphemes are efficiently separable, visible and contrasted. The similarity retrieval has been developed to contribute to both handwriting compression and writer identification. This work is currently integrated to a complete compression system that is dedicated to gray level ancient handwriting documents without information loss and that will be integrated in the MADONNE project in the coming days.

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