An Interactive Tool for Forensic Handwriting Examination

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***Abstract*— We introduce a tool for quantitative evaluation of handwriting features largely adopted during forensic examination of questioned documents. The tool is based on a model of handwriting generation and execution according to which handwriting is composed of elementary movements, called strokes, whose order and timing of execution has been learned and stored in the brain. Thus, what characterizes handwriting individuality, and therefore should be inferred from the samples available, is the way the sequence of strokes are executed. The tool does not aim at reaching a conclusion on the writer's identity when comparing two documents, but provides the quantitative evaluation of a set of features that can be used by the expert to support his/her conclusion. Although the tool is meant to proceed automatically from the scanned image of the document to the quantitative evaluation of the features, it is equipped with an interface that allows the expert to follow the automatic procedure step-by-step and even to modify the output of any step and to modify it in case it is deemed as incorrect. The tool automatically produces a customizable report to illustrate the procedure, the features computation and to show the computed features values in both numerical and graphical form.**

Keyword: forensic document examination; handwriting; writer identification;

I. Introduction

The principle handwriting identification is based upon has been defined as follows [1]:

"*When any two items possess a combination of independent discriminating elements (characteristics) that are similar and/or correspond in their relationships to one another, of such number and significance as to preclude the possibility of their occurrence by pure coincidence, and there are no inexplicable disparities, it may be concluded that they are the same in nature or are related to a common source*."

According to this definition, handwriting identification involves the definition of both the characteristics whose similarity has to be evaluated and the procedure to perform the evaluation.

As with regards to the set of characteristics, or features, they are more or less formally grouped according to the item they refer to: the whole document, the text lines, the words and eventually the letters or part of them [1-3]. These features, as well as the ones that are used in different countries in Europe and Asia, are empirical in nature, as they are the final outcome of a long process of filtering and categorization of the best practices, as they have been developed and used along the years by forensic document examiners. As they are intended for the use by humans, their definition is far to be an operational one, being often expressed in semantical terms rather than formally defined.

Similarly, the procedure for computing the features that need to be globally estimated are very seldomly described in algorithmic terms on well-defined entities extracted from the ink.

To clarify this point, let us consider the definition of the feature slant (or line of writing). This is a line-level feature defined as the angle between the baseline of the word and the horizontal margin of the document. Since the baseline is not visible, unless there is a ruling line, it must be inferred by the expert, thus introducing a certain degree of subjectivity in the evaluation. Similarly, it is not defined how to compute the slant of the whole text line starting from the slant of each word.

All together, these factors introduce a certain degree of subjectivity in the evaluation. Subjective evaluation does not mean that the results of properly conducted comparisons will be either unreliable or inaccurate. A carefully designed scientific testing has shown that professional document examiners (as a group) outperform lay-persons on handwriting identification [4]. However, the final decision depends greatly upon the expertise of the examiner, to the extent that different examiners may consider different set of features, assuming that some of them may be irrelevant, and/or different procedures for estimating their values. This (uncountable) amount of expertise introduced in the process by the examiner was deemed as one of the crucial issues when the reliability of the forensic examination of handwriting was questioned by the ruling of some courts in the US [5].

In order to reduce the influence of expertise during data collection, we introduce a tool for quantitative evaluation of the features currently used for handwriting identification. Recently, a comprehensive review of other software designed since the 1990s has been published [6] and it has shown that automatic tools made less success than cad software between the examiners. Our opinion is that this failure is related to different aspects, most of all the inconsistency between the measurement computed by the

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software and those measured by the experts. With respect to other tools that have been previously proposed and/or are routinely used in some organizations the tool proposed here is not meant to reach a final decision about the writer identity, nor to compute the features values on the basis of the examiner input. On the contrary, the tool assumes that fluency in handwriting emerges from the time superimposition of strokes, as suggested by the literature on handwriting generation [7-10], and aimed at automatically extracting the strokes from the handwriting and using them as basic units for computing the value of the features, in the very same way as the tests routinely performed in medicine. A sample (the handwriting) is taken, its basic components (the strokes) are automatically detected and eventually a set of features (at every level) are computed from those basic units by means of well-defined operational procedures. The results provided by the tool are eventually used by the expert as evidence for drawing the final decision.

The remaining of the paper is organized accordingly: in Section 2 we outline the protocol for forensic examination of document for putting the tool in the appropriate context. In Section 3 we describe the procedures for extracting the strokes from the ink, while in Section 4 we describe the procedures for computing the features of interest. Eventually, the conclusions summarize the main features of the current implementation and outline future developments.

II. Forensic Examination of documents

Forensic document examinations are mainly performed in order to establish the genuineness and the authorship of a document. The first step of the examination process should be aimed at establishing that no alternations, additions, obliterations and erasures appear and therefore that the document is genuine. These kind of analysis are realized with different techniques and equipment, for example chromatography and infra red spectroscopy. Once all the information about paper and ink lead to the classification of the document as genuine, the second step is to identify the author. As suggested by [2], the comparisons of questioned and known handwriting for determining the authorship are the most frequent examination type and it constitutes the 80% or more of the work load for many experts. Accordingly, a software tool for assisting examiner in the handwriting comparison step can be useful for reducing the time spent for an examination and defining a common practice in the analysis process. An examination performed with a software tool is an examination conducted on an image, i.e. a reproduction, of the original document. If the image is acquired with a common scanner, information about microscopic details are loss, therefore we have developed a tool that looks only to the document layout and to the shape of handwriting. Furthermore, it is the examiner and not the software to being called to give an opinion about the authorship of a document and therefore the examiner have to know how the measurement are performed. Accordingly, our tool allows to the examiner to manually correct the output of each process stage and it provides useful instruments for writing a report but it doesn't provide a similarity measure between the questioned document and the specimen.

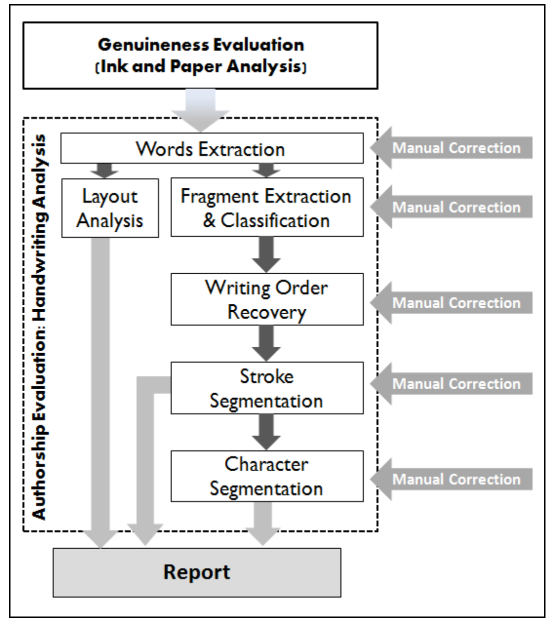

Figure 1. Forensic Examination process

III. Handwriting elaboration

As mentioned in the previous section, our tool implements the "*authorship evaluation stage"* as in fig. 1.

Different processes, which are aimed at automatically identifying the elementary movements produced by the writer, are executed on the acquired image of the document.

The output of each process is shown to the examiner that can modify it, if necessary. The set of processes performed by the tool are:

A. Words Extraction

The first step executed by the tool is the line and word segmentation based on the segmentation algorithm proposed in [11]. Each found word is enclosed by a clickable bounding box, as shown in Figure 2. If the word segmentation algorithm fails, the user can manually split a bounding box containing more than one word or merge two or more boxes containing different components of the same word.

B. Fragments Extraction and Classification

Often a word is not produced by keeping the pentip in constant contact with the paper, so as to have a continuous ink, but lifting the pen here and there while drawing. As a consequence, a word is composed by different types of ink namely isolated characters, cursive, dots, horizontal and vertical bars. Because the writing order recovery and the stroke segmentation can be performed only on isolated characters and cursive, we have presented in [12] an algorithm for extracting and classifying from a word image the sub-images that correspond to pieces of ink produced without lifting the pen.

In manual mode, the user can remove fragments badly classified as character or cursive and he can merge fragments that should be united by a semantically point of view.

C. *Writing Order Recovery*

In a previous work [13], an algorithm for writing order recovery was presented. The static handwriting of fragments labeled as isolated character and cursive is represented by its skeleton, which is then converted into a graph, whose arcs correspond to the skeleton branches, and nodes to either end point or branch point of the skeleton. Criteria derived by handwriting generation are then applied to transform the graph in such a way that it can be traversed from the first to the last node by using the Fleury's algorithm. At the end of this step, the ink of the fragment has been unfolded according to the reconstructed writing order.

In manual mode, the skeleton of the selected fragment is shown to the user that can suggest a different writing order by clicking on the end points and the branch points in the desired manner.

D. *Stroke Segmentation*

Given the sequence of points belonging to the ink, a stroke segmentation is performed by using an algorithm based on the concept of saliency introduced for modeling visual attention shift [14]. Following this approach, the electronic ink represents the scene the system is looking at, and its curvature represents the feature whose saliency is estimated. Thus, segmentation points correspond to the highest values of the saliency map. The obtained segmentation is much more invariant with respect to locally prominent but globally non-significant changes of curvature.

In manual mode, the user can delete and insert segmentation points, if necessary.

E. *Character Segmentation*

Once the elementary movements have been detected, it is possible to automatically associate each of them to the character they belong to if the user provides the transcription of the fragment under elaboration. In [15], a method that locates the position of the characters within a handwritten text by using a probabilistic approach that estimates the number of strokes for each character has been presented. As before, the user can manually correct the association between stroke and character. In Figure 3, the software interface for inserting the transcript of each fragment and the automatically character segmentation of one of them is shown.

IV. MEASUREMENTS

Once the handwritten text is segmented in words and the ink of each fragment is segmented in stroke, measurements are computed automatically and a report is generated. During this computation, the user is not allowed to interact with the tool, in order to guarantee that the measurements are not affected by the user intervention.

Different aspects of writing, in addition to the stroke sequencing and execution mentioned before, become automatic (habitual) with practice and all together constitute the means by which the questioned handwriting may be discriminated or associated with the known writing. 21 *discriminating elements* are suggested in [1] as the most employed and appropriate in the identification task. Some of these elements can be *observed* whereas others can be *measured* in the document. In the current implementation our tool includes only the subset of elements that can be measured, and for each of them the maximum, the minimum, the mean and the variance values are computed. We have divided the measurements in four groups depending on the "item" that they capture:

A. *Document level measurement*

The dimensions and uniformity of margins can be significant because different writers start and stop their writing at different locations. For example, some writers show consistent margins in every direction, others are not able to maintain a right margin. Some writers tend to occupy all the page, other to arrange the text in a portion of it. The dimension and the arrangement of margins are computed by our tool as follows:

- The left margin is the distance between the top-left point of the bounding box surrounding the first word of each line and the left edge of the sheet;
- The right margin is the distance between the top-right point of the bounding box surrounding the last word of each line and the right edge of the sheet;
- The top margin is the distance between the top-left points of the bounding boxes surrounding the words of the first line and the upper edge of the sheet;
- The bottom margin is the distance between the bottom-left points of the bounding boxes surrounding the words of the last line and the bottom edge of the sheet.

When blank or unruled sheets are used for writing a text, **the interlinear spacing** is another discriminating element to be evaluated. Given M text lines, it is measured by following these steps:

1. for each word i, the skew m_i as in [16], the center of mass com_i and the rightmost point rp_i lying on the line passing through com_i with skew m_i are computed;
2. for each line j, the best fit least square regression line associated with the set of point $\{(com_{1j}, rp_{1j}), \ldots, (com_{Nj}, rp_{Nj})\}$, with Nj number of words belonging to line $j \in \{0,\ldots, M\text{-}1\}$, is calculated;
3. because the best fitting line j and the best fitting line $j+1$ may not be parallel, the distance between them is a mean value.

B. *Line level measurement*

The **skew of the baseline** is an aspect in which writers introduce their own individuality, as explained by [3]. It is measured by the skew of the best fitting line described previously.

The **interword spacing** in a writing is not always uniform, some writers leave little space between words while others use larger spaces and therefore it is another aspect useful in the identification process. This spacing is calculated as the distance between the bounding boxes of two consecutive words. In [3], it is suggested to compare the spacing between words with the width of the letter "o" in order to classify them as narrow, normal, wide or a mixture.

Despite that, we prefer to compute the spacing as an absolute measurement and leave to the user the choice of compare it with a reference.

C. Word level measurement

The **interfragment** and the **interletter spacings** are the two measurements proposed by our tool for intraword spacing. The interfragment spacing is computed as the distance between the bounding boxes of two consecutive fragments belonging to the same word.

The width of each letter is measured instead of the interletter spacing, as suggested by [1], because the latter is affected by the method used for estimating it, whereas the width of a letter is a well-defined measure. The tool calculates it only if the user has provided the transcription of the fragment.

D. Stroke level measurement

Vertical dimension, proportions, relative heights are different expressions used to refer to measurements for characterizing the size of writing and the dimension of letters and parts of them [1].

We choose to implement these measurements at stroke level in order to give a formal definition of them.

First of all, the core, the upper and the lower regions of the word are estimated [16]. The height of the core region is a measurement of the **height of the central elements**. Then, each stroke is labeled on the basis of its position across these regions:

- a stroke starting in the core region and ending in the upper region is an *ascender up;*
- a stroke starting in the upper region and ending in the core region is an *ascender down;*
- a stroke starting in the core region and ending in the lower region is a *descender down;*
- a stroke starting in the lower region and ending in the core region is a *descender up;*
- a stroke starting and ending in the core region is a *center;*
- a stroke starting in the lower/upper and ending in the upper/lower region is a *pipe;*

The height of a stroke is computed as the difference between the y-values of its starting and ending points. The heights of ascender, descender and pipe are divided by the height of the central elements for computing the **relative heights.**

The inclination of the ascender and descender relative to the baseline is an estimation of the **writing slant.** As in a previous works [17], we used an ellipse for describing the shape of a stroke. In particular, the angle θ between the major axis of the best fitting ellipse, in the least-squares sense, and the baseline is used for estimating the slant of the stroke. The angle γ between the major axis of two consecutive stroke can be used for estimating their amount of time superimposition. The angle γ evaluated between an ascender up and an ascender down, or between a descender down and a descender up, can be useful for measuring the **amount of roundness** of a writing.

Figure 4 reports some of the measurements computed by the tool on the documents shown in Figure 2.

V. CONCLUSIONS

We have presented a tool for Forensic Handwriting Examination whose primary purpose is that of helping the examiner in collecting data from the documents under investigation. The tool works on the digital reproduction of a paper document, and computes a set of features largely adopted in forensic handwriting examination, at document, line, word and stroke level. The selected features are computed from a base representation of handwriting as a sequence of strokes, which, according to handwriting generation studies, are the most elementary units composing handwriting. Accordingly, and because the strokes are embedded into the ink, the tool includes algorithms to recover the sequence of strokes. Due to the complexity of the task, the algorithms used in the current implementation may introduced errors in both the reconstructed dynamics of handwriting as well as on the inferred sequence of stroke. For this reason, the tool is equipped with a graphical user interface that allows the expert to modify the output of the algorithms. Once the sequence of strokes has been computed, the tool proceeds automatically, so as to avoid any intervention of the user during the measurement, to compute the selected features and present the results in both numerical and graphical form. The final output of the tool are therefore the features values computed on both known and questioned documents to be used by the expert to reach his/her final conclusion.

The tool has been developed following studies on handwriting learning and execution, which suggest that there is a neural correlate of the sequence of stroke assumed by computational model of handwriting generation. Accordingly, the features commonly adopted by Forensic Handwriting Examiners have been expressed quantitatively in terms of the shape of the strokes and their spatial relationship. From this point of view, thus, the tool may represent a valuable help in reducing the subjectivity in collecting the data that greatly reduces the perceived "objectivity" of forensic document examination with respect to other computational forensic methods and tools routinely used in courts.

Our next step will be to investigate to which extent some of the features suggested by the best practices and not considered in the current implementation can be measured from the basic representation of handwriting, as well as to analyze the behavior of the features values when comparing two documents in order to find some measurements of the similarity between them, and to incorporate these measurements into the tool, for providing the Forensic Document Examiners with more data to draw their conclusions about the authorship of the documents.

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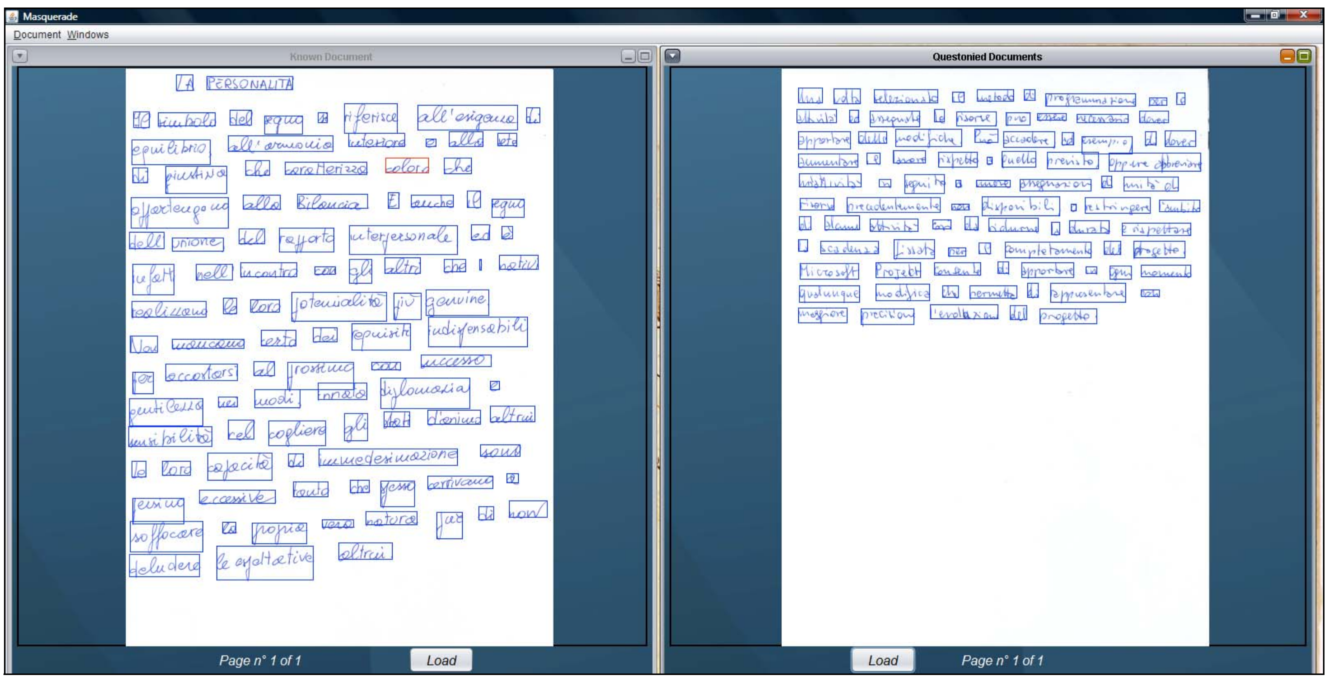


Figure 2. The Know and the Questioned Documents. Each word is surrounded by its bounding box.

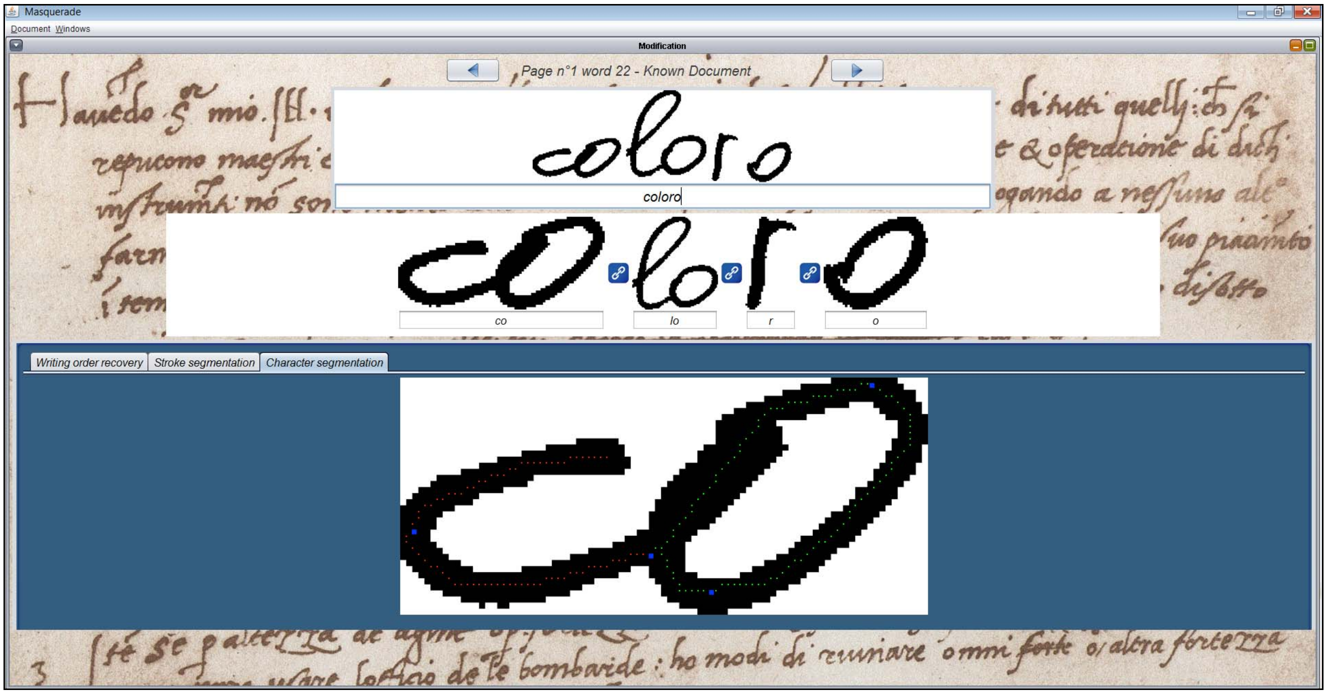
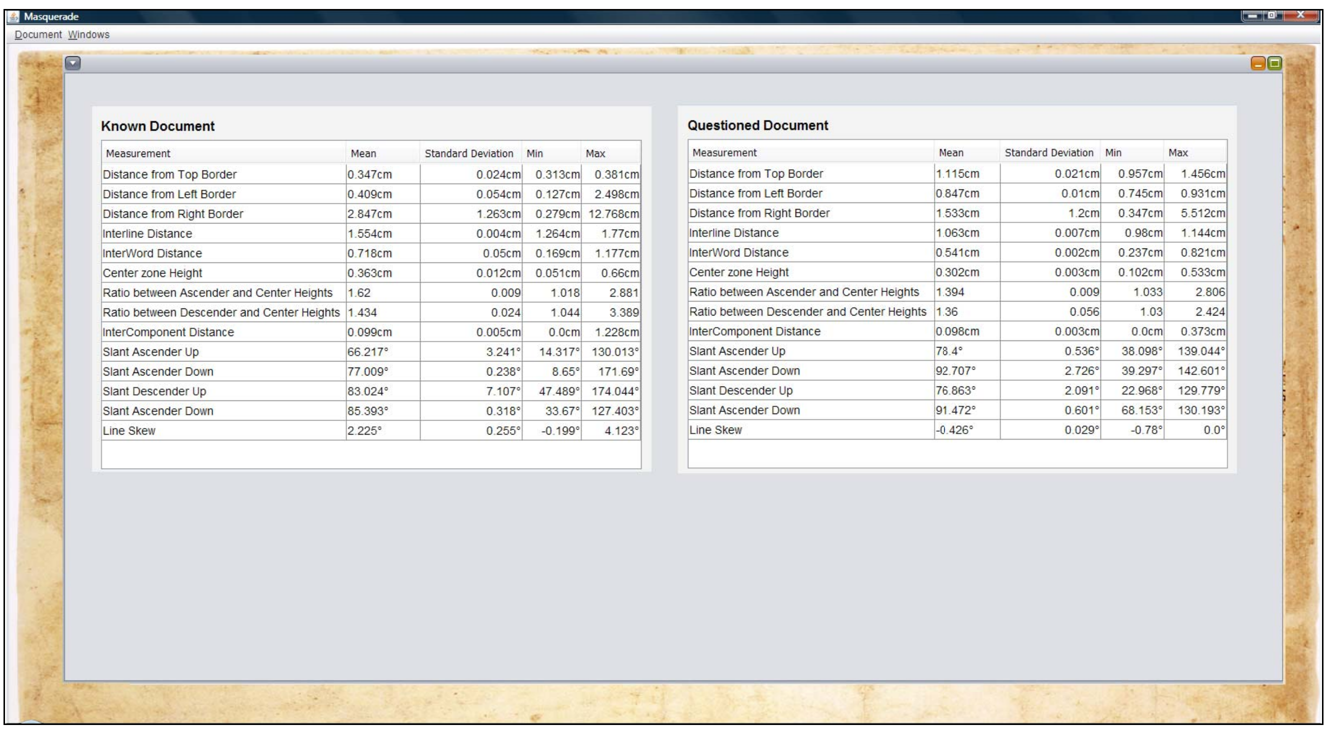


Figure 3. A word extracted by the Known document. The user has inserted the transcript of the word (“coloro”) and the tool allocates the letters to the right fragments. Eventually, each stroke is assigned to the character it belongs to. In the figure, the first two stroke are assigned to the character “c”, and the last three to the character “o”



Masquerade

Document Windows

Known Document

Measurement	Mean	Standard Deviation	Min	Max
Distance from Top Border	0.347cm	0.024cm	0.313cm	0.381cm
Distance from Left Border	0.409cm	0.054cm	0.127cm	2.498cm
Distance from Right Border	2.847cm	1.263cm	0.279cm	12.768cm
Interline Distance	1.554cm	0.004cm	1.264cm	1.77cm
InterWord Distance	0.718cm	0.05cm	0.169cm	1.177cm
Center zone Height	0.363cm	0.012cm	0.051cm	0.66cm
Ratio between Ascender and Center Heights	1.62	0.009	1.018	2.881
Ratio between Descender and Center Heights	1.434	0.024	1.044	3.389
InterComponent Distance	0.099cm	0.005cm	0.0cm	1.228cm
Slant Ascender Up	66.217°	3.241°	14.317°	130.013°
Slant Ascender Down	77.009°	0.238°	8.65°	171.69°
Slant Descender Up	83.024°	7.107°	47.489°	174.044°
Slant Ascender Down	85.393°	0.318°	33.67°	127.403°
Line Skew	2.225°	0.255°	-0.199°	4.123°

Questioned Document

Measurement	Mean	Standard Deviation	Min	Max
Distance from Top Border	1.115cm	0.021cm	0.957cm	1.456cm
Distance from Left Border	0.847cm	0.01cm	0.745cm	0.931cm
Distance from Right Border	1.533cm	1.2cm	0.347cm	5.512cm
Interline Distance	1.063cm	0.007cm	0.98cm	1.144cm
InterWord Distance	0.541cm	0.002cm	0.237cm	0.821cm
Center zone Height	0.302cm	0.003cm	0.102cm	0.533cm
Ratio between Ascender and Center Heights	1.394	0.009	1.033	2.806
Ratio between Descender and Center Heights	1.36	0.056	1.03	2.424
InterComponent Distance	0.098cm	0.003cm	0.0cm	0.373cm
Slant Ascender Up	78.4°	0.536°	38.098°	139.044°
Slant Ascender Down	92.707°	2.726°	39.297°	142.601°
Slant Descender Up	76.863°	2.091°	22.968°	129.779°
Slant Ascender Down	91.472°	0.601°	68.153°	130.193°
Line Skew	-0.426°	0.029°	-0.78°	0.0°

Figure 4. Some measurements performed by the tool on the documents shown in figure 2.