Ink-deposition Analysis Using Temporal (online) Data

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Abstract

This paper focuses on a new computational method for discovering and evaluating ink-trace characteristics related to the writing process. Typically, these ink-trace characteristics are inner ink-trace morphology, trace width and / or ink-intensity variations, but also specific stroke phenomena, such as ink drops, feathering and striations. The aim of the evaluation is to provide objective and reproducible analysis results for stroke morphologies in order to detect skilled forgeries and technical copies. The influences of different kinds of writing material, like the ink type used, is taken into account. By means of recorded, temporal (online) data, segmented ink traces are sampled equidistantly, and local ink-trace characteristics are encoded in one feature vector per sample record. These data establish a sequence which faithfully reflects the spatial distribution of ink-trace characteristics and solves problems of methods previously available. Dynamic Time Warping is implemented for the verification of two feature-vector sequences. The proposed method works towards (1) detailed studies of ink-deposition processes, (2) objective testing procedures in forensic practice, and (3) the advancement of skilled forgery detection for automatic bank-check processing.

Keywords: forensic, signature verification, combined on/offline analysis, stroke morphology

1. Introduction

Mimicking another person's handwriting movements is very difficult due to the fact that they involve individual kinematic and force-time functions, e.g. [39, 41]. Therefore, in forensic investigation the deduction of handwriting movements from the residual ink trace on paper is considered as the key to drawing conclusions about the authorship of a questioned handwriting or the authenticity of disputed signatures [21, 29]. Experimental testing of signatures, e.g. [27, 28], has shown that the most reliable features for distinguishing between authentic specimens and skilled forgeries are the rhythm of the pen force and the overall line quality. Hence, it is important to establish objective testing procedures that make it possible to derive and validate information from an ink trace in order to draw conclusions regarding the previously performed biomechanical writing processes.

Various approaches to recover temporal information from static handwriting specimens already exist. Procedures in forensic examination are mainly based on the microscopic inspection of the writing trace and hypotheses regarding the underlying writing process, e.g. [21, 22, 29]. The techniques applied in the field of image processing and pattern recognition can be divided into (i) mathematical methods for estimating the temporal order of stroke production [1, 3, 23, 25], (ii) methods inspired by motor-control theory for recovering temporal features on the basis of stroke geometries, such as curvature [32, 34], and (iii) methods for analyzing stroke thickness and / or stroke-intensity variations [2, 7, 19, 37, 43]. However, these previous works in the field of image processing did not sufficiently take into consideration the physical properties and influences of writing materials like pen and ink. In addition, they did not preserve the spatio-temporal relationship of the deposited ink.

The approach presented here is inspired by forensic expertise and elaborated by digital signal processing and pattern recognition. In accordance with an *Ink-Deposition Model* [14], which incorporates the physical ink-deposition process, handwritten traces are normalized and segmented into regions of relatively similar ink intensity. In addition, a fundamental approach for the combined analysis and cross-validation of recorded temporal writing / tracing movements and digitized ink traces will be established.

The paper is organized in five sections. The method for ink-deposition analysis using temporal (online) data is outlined in Section 2. Core Algorithms are described in the subsequent Section 3. The experimental setup and first results are given in Section 4. The final Section 5 provides the conclusions and hints to further research.

2. Method overview

Recorded writing movements can be used for the analysis of ink traces. There are a number of possible analysis procedures that take temporal information into account. Such methods can be subdivided into three primary groups, i.e. (1) the reconstruction of the stroke sequence [42, 30], (2) the tracing of the handwritten ink traces [19], and (3) the assignment of temporal handwriting characteristics, e.g. relative pen force and writing velocity to static ink-trace characteristics [12]. Addition-

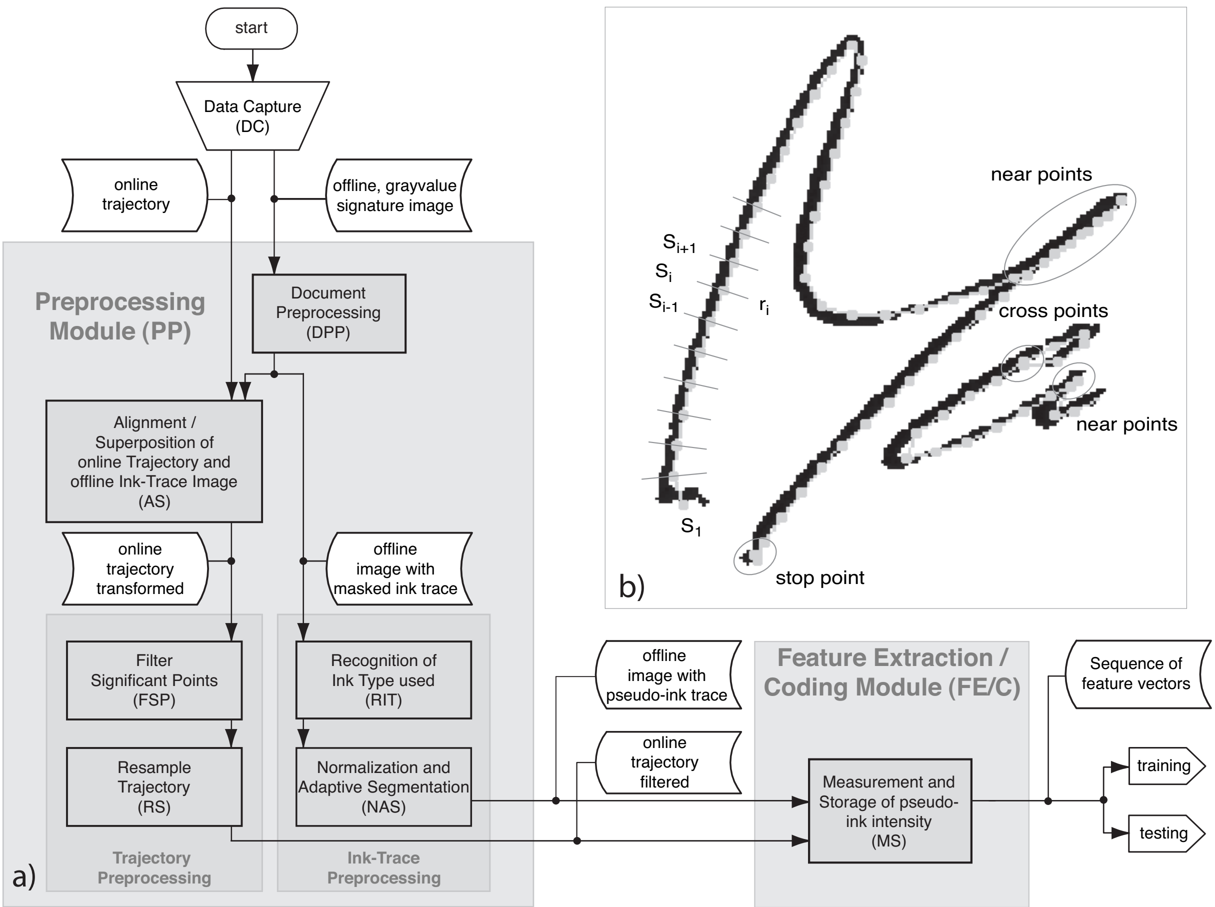

Figure 1. a) Schematic overview of the preprocessing and feature extraction applied in ink-deposition analysis. The consideration of recorded writing movements demands specific methods for preprocessing the online trajectories. In addition, the offline ink traces have to be normalized. b) Preprocessed ink trace and superimposed online trajectory. Ambiguous stops as well as the cross and near points are marked. In addition, sample points and rulers are illustrated, and the normalized ink deposit is sensed.

ally, the origin of the online handwriting data has to be taken into account. The following scenarios can be distinguished: (A) Simultaneously produced on- and offline data, i.e. written with an ink pen on a sheet of paper placed on an electronic tablet, (B) Traced online data entered by a forensic expert by retracing an offline sample, (C) Online samples written by the same person at an earlier / later date, and (D) Online samples written by another person. The combined usage of on- and offline data offers a wide range of analysis and cross-validation methods. A new computational method is proposed here for analyzing the stroke morphology of signatures and, in particular, for analyzing the relative amount of ink deposited on paper. It supports the reconstruction of the stroke sequence as well as the sensing of the ink trace (1, 2) by means of simultaneously produced or traced online data (A, B). For a schematic overview of the approach, especially for preprocessing and feature extraction, see Figure 1a. In detail, the method comprises the following steps:

Data capture (DC) Optical scanning of the paper document carrying the ink trace. The online trajectory is recorded by means of an electronic pen tablet.

Preprocessing module (PP)
- *DPP* Offline document preprocessing for the computation of the ink-trace mask, especially for removing backgrounds and imprints using methods described in [13].
- *AS* Alignment / Superposition of on- and offline data for sensing the ink flow (Figure 1b). It has to be taken into account that currently available tablet technologies are partly restricted with regard to their signal fidelity, and that ink tracing, e.g. performed by a forensic expert, is not sufficiently accurate, so that the captured pen position cannot be used in a computational method. Thus, scaling, rotating, translating and non-linear morphing of the online sample position is demanded that facilitates the alignment / superimposing of online pen trajectories and offline ink traces (compare [9]).
- *FSP / RS* Filtering and equidistant re-sampling of the online data in order to provide equally distributed measurement points and to indicate *stroke intersections, cross-* and *near points*, and *stop points* (Figure 1b). The challenge of near points in offline analysis was discovered by Doermann et al. [6]. However, online data can help to handle arising difficulties in the offline analysis later on. It

must be noted that for the filtering of near and cross points some heuristics about the digitized ink trace and its line width are taken into account. It results in the marking of an extended number of samples of the online trajectory (see Figure 1b).

- RIT Recognition of the ink type used [10] in order to determine whether the stroke-morphology characteristics are suitable for a more detailed analysis that takes the appropriate Ink-Deposition Model [14] into account.

- NAS Normalization and adaptive segmentation of the ink trace in order to quantize ink intensities. In this way the ink trace is converted into pseudo-ink segments that become independent of the particular ink used. For details see the upcoming Section 3.

Feature extraction and coding module (FE/C)

- MS Measurement of normalized ink intensity along the superimposed online trajectory, and storing of the sensed characteristics in a sequence of feature vectors. These methods for feature extraction and encoding into numerical parameters, which represent the relative ink deposit on paper, are covered by Section 3.

Analysis and validation module (AV)

- VFS Validation of the sequence of feature vectors obtained from a questioned signature specimen by comparing them with those of a known reference sample. The procedure is also described in Section 3. The cross-validation of sensed ink-trace characteristics with real temporal handwriting information, such as pen-tip force and writing velocity will be left open for further research.

3. Core Algorithms

For a computer-based analysis the ink deposits need to be encoded into feature vectors. These must be valid for each individual signature pattern. Disturbing influences need to be eliminated in advance. The features have to be normalized to facilitate the cross-validation of different probes, e.g. those written with specific kinds of pens and ink. The procedures described in the following focus on exactly these requirements, especially on (i) the normalization of ink-trace intensities, on (ii) the sensing of ink deposit along the trace, and on (iii) the cross-validation of encoded ink deposits.

NAS Normalization and adaptive segmentation of the ink trace: In order to ensure validity regardless of the particular pen / ink type used, ink traces extracted from document backgrounds need to be normalized. Different approaches can be found in literature, for example, the *Densitron*-approach by Grube [17, 18], and threshold techniques applied, for instance, by Sabourin et al. [37] or by Ammar et al. [2]. The latter two are adaptive methods, but unfortunately they do not appropriately take into consideration the characteristics of the ink-intensity distribution. Particularly the distinct characteristics of ink-intensity-frequency plots produced by solid, viscous and fluid inks, are not taken into account (compare [14]). The methods only assume the presence of so-called *high-pressure regions* that correspond to greater pen-tip forces. The high-pressure regions are defined as ink intensities exceeding a threshold P_0. The threshold P_0 is either determined by the well-known Otsu method [31], by Ammars α-cut procedure [2] or empirically preset, e.g. [4, 19, 40]. In contrast, the previously mentioned *Densitron*-approach is not adaptive. It only represents an intensity range, e.g. 64 intensity levels, by one pseudo-color. Since these intensity ranges were predefined, and not adaptively adjusted to the support, the mean or median intensity of the ink-intensity distribution under investigation, traces by different pens / inks could not be cross-validated. Nevertheless, the basic idea of the *Densitron*-approach could support the modeling of the entire ink trace. To allow for a normalization and validity irrespective of the particular pen / ink used, the approach was further elaborated by the author [11]. In addition, a pilot study was conducted and the newly derived *adaptive Densitron* procedure was compared with an alternative approach as well as with the method proposed by Ammar et al. [2]. Further discussions on the Otsu method [31] are unnecessary, since the limitations of this method in handling heavily skewed distributions have already been addressed in [14].

For a formal description of the methods investigated in the pilot study, let us first define a digital image $I(x, y)$ with $0 \leq x < X$ and $0 \leq y < Y$. The background was removed in order to filter a set T of image coordinates ($T \subset I(x, y)$) that belong to a digitized ink trace. For the normalization of ink-trace intensities $I(x, y)$ a transformation into so-called pseudo-ink intensities $\tilde{I}(x, y)$ was performed. Afterwards, for each T the intensity-frequency plot was computed by

$$h(k) = \#\{(x, y) | I(x, y) = k; (x, y) \in T\}$$

with $0 \leq k \leq g_{\text{max}}$. The derived ink-intensity distribution provides the basis for the upcoming normalization. Specific procedures in accordance with *(NAS 1)* Ammar's *α-cut procedure*, *(NAS 2)* the *adaptive Densitron with equal range* and *(NAS 3)* the *adaptive Densitron with equal area* are detailed in the following.

Ad. NAS 1 – α-cut procedure: The approach proposed by Ammar [2] is defined as:

$$H(k) = \frac{h(k)}{\max_k h(k)}$$

$$P_0 = \max_k \left(\{k \mid H(k) \geq \alpha_{\text{cut}}\} \right)$$

Studies on various ink distributions have revealed that dubious segments occur especially in the case of writers who "glide" across the paper, since the intensity distribution is shifted to the right and therefore almost the entire ink trace is falsely interpreted as high-pressure region.

Ad. NAS 2 – Adaptive Densitron with equal range: Our first implementation of an adaptive Densitron was directly inspired by the original approach; the support of the distribution was segmented into a number N of ranges of equal size:

$\Delta s = \frac{\max_k(\,\text{support}(h(k))\,) - \min_k(\,\text{support}(h(k))\,)}{N}$ with

$\text{support}(h(k)) = \{k \mid h(k) > 0, \quad k = 0, \ldots, g_{\max}\},$

$s_0 = \min_k(\,\text{support}(h(k))\,)$ and

$s_i = \{k \mid s_0 + (i-1)\Delta s \leq k \leq s_0 + i\Delta s\}$ with $1 \leq i \leq N$

The method, however, does not take the skewness of the distribution into account and yields weak segmentation results for viscous and fluid inks.

Ad. NAS 3 – Adaptive Densitron with equal area: The final version of the adaptive Densitron was designed in such a way that for the given $l_0 = 0$ and $l_N = 254$, l_i segments are chosen by

$$\forall_{i=2,\ldots,N}\left(\sum_{k=l_{i-1}}^{l_i} h(k) = \sum_{k=l_{i-2}}^{l_{i-1}} h(k)\right)$$

This approach ensures the consideration of the specific characteristics of ink-intensity distribution and facilitates a reliable ink-trace normalization and transformation into pseudo-ink segments. Consequently, the cross-validation of writing traces produced with different pens / inks becomes feasible.

MS Measurement / Storage of pseudo-ink intensity: In order to support an automatic validation of ink deposits, the pseudo-ink segments have to be sensed and represented by sequences of the numerical feature vectors. Different approaches can be chosen to create these sequences, and therefore pilot tests were carried out to study three of them: *(MA 1)* the *x-projection*, *(MS 2)* the *vertical scan* and *(MS 3)* the *recovering of stroke sequences.* As a consequence, we decided to use online data for creating the feature sequences.

Ad. MS 1 – X-Projection: According to Ammar et al. [2] all segments of similar pseudo-ink are projected onto the x-axis of the image. The projection profile was scanned in horizontal direction, and thus the frequency of elements per image row determines the x-projection sequence. The sequence length corresponds to the horizontal extension of the signature pattern. This method is highly insensitive to local characteristics of pseudo-ink segments. Particularly the size of segments and their spatial distribution are poorly represented (compare Figure 2). As observed in the previous empirical studies [9], forgers do not always apply more pen-tip force, and their writing velocity is not necessarily reduced, which would lead to a greater amount of ink deposit. Rather, forged signatures are subject to local variations and adaptation strategies that correlate with the complexity of the motor task. Hence, he / she performs movements with more force impulses and pauses, resulting in small pseudo-ink segments, distributed along the entire writing trace. Applying the x-projection strategy for sensing ink-trace characteristics does not lead to an adequate representation of these specific phenomena, as demonstrated in Figure 2.

Ad. MS 2 – Vertical scan: In accordance with Sabourin et al. [36], distributed segments are collected by vertical scanning, similar to standard image filtering. The size of each pseudo-segment (amount of image elements) is stored. The number of segments within the image determines the length of the sequence. In contrast to the first approach, each segment is handled separately. However, the location of the segment is not represented adequately, and the approach is not immune to slight local variations. For example, a small shift of a segment can lead to a total disorder of the collected segments (compare Figure 3). Even a slight modification of the approach by additionally storing the x- and y-coordinate of the center of gravity for each segment, and by subsequently taking into consideration the spatial distribution of the segments, did not yield any relevant results.

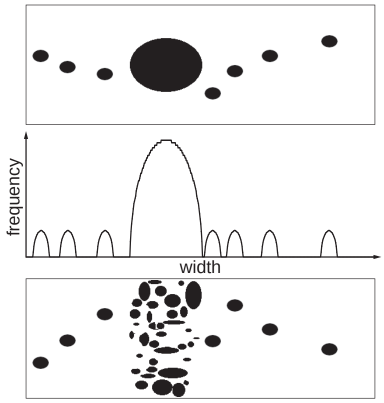

Figure 2. Feature-sequence creation for distributed connected components. The *X-Projection* [2] leads to a loss of spatial distribution, and larger and smaller segments cannot be differentiated.

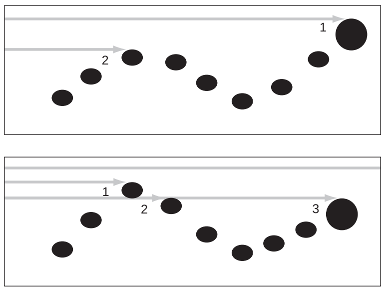

Figure 3. Feature-sequence creation for distributed connected components. *Vertical Scanning* [36] can lead to false representations of the order, if the overall pattern is slightly distorted.

Ad. MS 3 – Recovery of stroke sequences: No doubt, a more natural image-scan path for gathering the pseudo-ink segments would follow the writing trace. A variety of mathematical methods [1, 3, 23, 25, 34] for detecting the stroke sequences of handwritten words have been published. So far, attempts to transfer these approaches to signatures have not been successful, since European, and particularly Latin signatures, are frequently very complex, illegible man-made patterns. The underlying heuristics and optimization criteria are not robust with regard to complex trace intersections. Note that even in some difficult cases in forensic casework, human experts are barely able to reestablish the order of the ink traces. To deal with such difficulties Doermann et al. [7, 19] proposed a manual tracing of writing traces. This continues to be an adequate solution for a forensic assistance system, but it is inapplicable for automated check processing in banks. In addition, it can be extremely labor-intensive if a large amount of handwritten text is to be analyzed, e.g. in forensic applications where handwriting and signature probes are taken from suspects. Fortunately, modern electronic devices bring some relief. Electronic pens with standard ballpoint refills are now available. These can be employed while taking writing probes in criminal investigations, and they can also be employed for signing a bank check at the counter. In this way simultaneously produced on- and offline data samples become available and can be analyzed in a sophisticated manner [16, 19, 45].

In order to measure / sense the normalized ink deposit along the writing trace, sample points S_i of the superimposed and spatial-equidistant resampled online trajectory S of length I are employed. The ink sensing is inspired by Doermann [5] who studied ink-intensity profiles orthogonal to the trace direction. Elaborating on this, the direction β_i for a specific measuring line r_i in sample point $S_i\{x_i, y_i\}$ is defined as:

$$\beta_i = \frac{1}{2} \arcsin \sqrt{\frac{(y_{i+1} - y_i)^2 + (x_{i+1} - x_i)^2}{(y_i - y_{i-1})^2 + (x_i - x_{i-1})^2}}$$

whereby $S_{i-1}\{x_{i-1}, y_{i-1}\}$ and $S_{i+1}\{x_{i+1}, y_{i+1}\}$ denote the prior and succeeding sample of S_i, respectively. For the first sample S_1 and last sample S_I in the online trajectory the orthogonal of the related step segment is used. Along the defined 1-pixel-wide ruler r_i, which is a Bressenham line in direction β_i, the frequency of pseudo-ink-trace intensities is determined. The obtained frequency plot $v_i(k)$ per sample S_i is encoded in a feature vector $\vec{v}_i$ of length N. This vector length N corresponds to the number of pseudo-ink intensities.

$$\begin{aligned} v_i(k) \quad &= \quad \#\{(x, y) | \tilde{I}(x, y) = k; (x, y) \in r_i\} \\ \text{with} \quad & \quad 0 \leq k < N \end{aligned}$$

Subsequently, the ink deposit along the trace is stored as sequence $\{S_i\}$ of feature vectors $\vec{v}_i$. The quantization of the original ink-intensity profile ensures (i) validity irrespective of the pen used, (ii) fast / easy numeric analysis and (iii) greater robustness in the upcoming cross-validation of ink traces.

An alternative approach for sensing the ink deposit along an online trajectory needs to be mentioned here. In [19], Guo et al. propose the utilization of pen records obtained by the manual tracing of the digitalized ink strokes. They do not refer to any preprocessing of the online trajectory. The careful consideration of the approach shows that: (i) due to the search of near “dark points” the sampling along the ink trace may not be equally distributed. Specific trace segments can be over- or underrepresented in the final feature sequence. (ii) The threshold for determining “dark points” is a fixed one and may not adequately model the underlying ink-deposit characteristics. In the best of cases it may not be robust, if different ink colors of ballpoint-pen refills, like light blue and black, are used for writing. The computational method proposed in this paper eliminates these drawbacks.

VFS Validation of the sequence of feature fectors The comparison of questioned and known reference signature samples presupposes an appropriate verification method. Particularly the chosen representation, calls for the employment of well-established verification techniques in online signature analysis. A close look at the relevant literature, e.g. [8, 20, 26, 33, 38, 44] revealed that *Dynamic Time Warping (DTW)* and *Hidden Markov Models (HMM)* are frequently used. Both approaches facilitate a non-linear or stochastic correlation of time series with varying data lengths. Since the statistical properties of a signature and the underlying statistical model are difficult to determine on the basis of a limited amount of reference signatures per genuine writer, HMM approaches are not considered as reliable for the application domain discussed here. Note that feasibility studies in banks, which were conducted by our industrial partners, revealed that 3 - 5 reference signatures per account holder are manageable. Larger amounts, e.g. 20 reference samples as reported in some academic studies, are definitely not acceptable. Furthermore, it has to be taken into account that in forensic casework the number of adequate reference specimens can be restricted to just one signature. Thus, exhaustive statistical analyses, as needed for HMM approaches, are not applicable and therefore the focus here will be on DTW.

4. Experimental Results

In order to lay the foundations for inferring kinematics and kinetics from the residual ink trace, the following experiment will focus on the stability of ink distributions. As an extension of our experiment performed in [15], it seemed appropriate to investigate to which extent the line quality of signature samples will differ if they are written with exactly the same movements, e.g. by the robot, but by using different pens with the same ink type. The same data set as for stroke-phenomena analysis [15] was used. 26 ballpoint pens were taken to produce 10 signature probes per pen by means of a writing robot. This robot reproduces exactly the same pen trajectory and pen-force time function [9]. The experiments were conducted with 80 g / m^2 white copy paper and a soft writing pad, consisting of five of these paper sheets. After the robotic signature synthesis the paper sheets were optically scanned, using a calibrated image scanner with a spatial resolution of 300 dpi and 8 bit grayvalues. In a preparative step, the writing movements of the robot were recorded by an electronic pen-tablet (200 Hz sampling rate and 2540 dpi spatial resolution), thus matching online data were available for superimposing, sensing and analyzing the ink traces. In accordance with our pilot study [35] the sample distance was set to 10 units. For the chosen spatial image resolution of 300 dpi this sample distance corresponds to one probe per 1 mm ink trace. Subsequently, the preprocessed online data were used to sense normalized ink traces. The obtained values were stored in feature sequences for automatic comparison. Furthermore, the decision threshold for the DTW-approach needed to be determined in advance, in particular to differentiate between match and no-match of the normalized ink deposits. For this purpose, five pen probes out of the 26 produced were chosen at random. From these just five specific samples (even numbers only) were used to determine the decision threshold. The Derivative-DTW [24] was used to determine the average distance between two ink deposits produced by one pen probe. In addition, the standard deviation of the obtained distances was computed. Finally, the decision threshold between match and no-match was set to the average distance with a tolerance interval of 1.75-times of the average standard deviation of the distances.

Table 1. Results of the ink-deposition analysis of signatures produced by the robot with 26 different ballpoint pens and 10 samples each.

	Ink	
	intra-group	inter-group
Median	100.0 %	93.2 %
Quantil 03	100.0 %	88.8 %
Min	30.0 %	16.0 %

Experiments were conducted to compare the normalized ink deposits of all samples produced with one pen (intra-group), and of all samples produced with the 26 different ballpoint pens (inter-group). The results are listed in Table 1. The ink deposits of samples written with the same pen are highly concurrent and yield a median recognition rate of 100.0 %. For the cross-validation of samples written with different pens, the recognition rate drops slightly to 93.2 % (compare Table 1). A closer examination revealed that very often the first trace samples per pen probe produce rather mediocre recognition results. In these cases the ink was not properly extracted from the ink chamber and, as a consequence, less ink was deposited on the paper (ink-free begin strokes). Since specific characteristics of a pen can cloak the (bio)-mechanical effects, it is always advisable to check for defects in the writing instrument. Taking this fact into account, one can conclude that similar writing movements will lead to similar ink deposits on paper, even if different pens of the same ink-type class are used.

5. Conclusions

The new computational method proposed in this section aims at the evaluation of ink-trace characteristics that are affected by the interaction of biomechanical writing and physical ink-deposition processes. The analysis has focused on the ink intensity, which is sensed along the entire writing trace of a signature. This specific analysis was motivated by empirical findings in the field of forensic science, which revealed that mimicked handwriting, which is produced less fluently with many pen-force pulses, will cause disturbances in the inner ink-trace characteristics. In contrast to previous attempts at establishing a computer-based method, the approach presented here introduces new concepts in order to improve the reliability and reproducibility of analysis results. Especially the usage of superimposed, filtered online data makes it possible to take the stroke sequence into consideration. The adaptive segmentation of ink-intensity distributions takes the influences of different writing instruments into account and supports the cross-validation of different pen probes. The analysis is firmly rooted due to the compliance with rules of digitalization and due to sophisticated methods for the removal of document backgrounds and imprints. Regarding the method's reliability further improvements are to be expected if (i) the number of ink-sensing points is increased and (ii) the ink deposit is averaged over a local area of the trace segment.

From the overall results one can conclude that the proposed computational method is suitable for the analysis of ink deposits along the writing trace. This is also supported by our initial studies on the stability of single stroke phenomena, such as ink drops, striation or feathering [15]. Studies in the forensic field have hitherto been of a descriptive nature. This paper provides all the prerequisites for a systematic analysis of ink deposits under strictly controlled conditions. Along with the experimental results obtained, it lays the methodological foundations for further research, development and forensic casework in the computer-based analysis of signatures. The procedures facilitate elaborate studies on the biomechanics and physical interaction processes, which should especially focus on the validation of samples written by the same human writer with different pens, but also on the cross-comparison of authentic and mimicked handwriting.

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