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Author

Nguyen, Vu, Blumenstein, Michael

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Techniques for Static Handwriting Trajectory Recovery: A Survey

Vu Nguyen
School of ICT
Griffith University, Australia
Vu.Nguyen2@student.griffith.edu.au

Michael Blumenstein
School of ICT
Griffith University, Australia
M.Blumenstein@griffith.edu.au

ABSTRACT
On-line handwriting recognition systems are usually better than their off-line counterparts thanks to the accessibility to dynamic information such as stroke order, velocity, acceleration, and pressure. Whilst the exact value of velocity as well as acceleration or pressure is unlikely to be recoverable, the temporal order of the strokes or the pen trajectory is shown to be more promising for recovery. The experimental results reported in the literature suggest that the recovered pen trajectory actually improves the off-line recognition accuracy. This survey presents an overview and discussion of pen trajectory recovery methods developed to date.

General Terms
Algorithms Documentation, Performance

Keywords
Off-line recognition, handwriting tracing, trajectory recovery

1. INTRODUCTION
The research in automatic handwriting recognition has been intensively pursued for nearly four decades and has obtained some significant achievements [1]. Successful applications include: postal address recognition [2], on-line signature verification, historical document recognition and form processing.

Automatic recognition systems can be categorised as being on-line or off-line based on the availability of dynamic information. On-line recognition is usually performed using temporal spatial information generated from the movement of a stylus on the surface of an electrostatic or electromagnetic tablet. Depending on the hardware, this signal stream of information may include: pen-inclination, pressure, velocity, acceleration, movement direction, number of strokes. From such information, the correspondent static image could be simulated [3] using ink deposition models and trajectory interpolation functions.

Unlike its on-line counterpart, off-line recognition employs only the static images captured by optical devices such as a camera or scanner. Due to the absence of dynamic information, the accuracies of off-line recognition systems could not be as high as on-line recognition [1]. As a trade-off, the on-the-fly collection of dynamic information restricts the applications of on-line recognition and gives off-line recognition certain unique advantages such as the ability to capture information remotely and conveniently.

The success of on-line systems [1] encourages the recovery and utilisation of dynamic information, such as pressure [4] and, especially, stroke order to improve the performance of off-line recognition systems. Research in the field of psychology also suggests that humans' perception of dynamic information from static images assists in the recognition of characters [5]. It is strongly believed that if the trajectories are properly recovered, the performance of automatic off-line handwriting recognition systems could significantly be improved [6-9]. Handler *et al.* [10] reported a recognition performance downgrade when off-line data was simulated using on-line data. Experimental results from [7, 11] later confirmed that the time ordering of the signal contains important information for the recognition of handwriting.

Despite a large number of successful applications, such as word segmentation and recognition [6, 11], character recognition [12], numeral recognition [13, 14], writer identification [15] off-line signature verification [16-18], overlapped handwriting extraction, etc..., off-line handwriting trajectory recovery remains an open and challenging problem.

2. PREPROCESSING
Similar to many other handwriting recognition problems, the performance of a trajectory recovery technique is affected by the quality of the handwriting static image.

It is generally agreed that preprocessing is necessary to stabilise image quality for further analysis [1]. This process may include, but not be limited to, gray-scale conversion, binarization, noise removal, broken stroke restoration [19], contour smoothing.

Conversely, some researchers argue that preprocessing reduces the robustness of a trajectory recovery system. A popular preprocessing operation such as binarization would deteriorate or even destroy valuable clues such as intensity consistency, continuation, and feathering whilst these clues could possibly be extracted and utilised using gray-scale images [20]. As a result, gray-scale based trajectory recovery techniques have been investigated [21-23].

3. APPROACHES

Trajectory recovery techniques found in the literature usually consist of two major processes: local examination and global reconstruction.

Local examination provides the essential information which will be referred in the global reconstruction phase. This often includes the detection and analysis of junctions or ambiguous zones, endpoints, double-traced lines but can also be extended to gray level consistency, striations, feathering, pressures, and accelerations [24].

In global reconstruction, the overall trajectory is determined using the information obtained from local examination. The outcome of this process can be a list of ranked trajectory candidates which may further be analysed using a knowledge-based module [7].

In [25], Rousseau *et al.* investigated the knowledge inherent in handwritten letters to evaluate its effectiveness in trajectory recovery. In some research on signatures [16, 26, 27], on-line information previously obtained in a registration process has been utilised for the purpose of off-line trajectory recovery. Adopting this approach, Qiao *et al.* reported a verification rate of 92.6%. Munich and Perona [28] tracked the stroke order of signatures with the assistance of a camera.

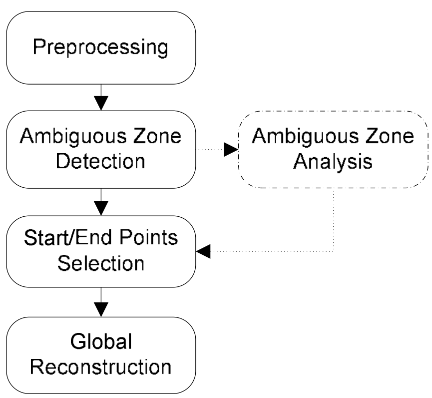

Figure 1. Common Components of a Trajectory Recovery Approach

Doermann [24] suggested that trajectory recovery techniques can produce useful information when obtained from stroke and sub-stroke features as well as knowledge about the writing process. The detailed taxonomy of temporal clues can be found in [24]. Despite the promising outcomes, examining the handwriting at a sub-stroke level is considered to be very computationally costly, Plamondon and Privitera noted [6].

3.1. Skeleton

As presented in the literature, the very first work in handwriting trajectory recovery [13, 14, 29, 30] employed 1-pixel line width thinned images, namely the skeleton.

The main advantage of skeleton-based approaches is computational efficiency whilst maintaining acceptable geometric and topological attributes [31]. Ideally, the skeleton should be identical to the original pen tip trajectory [32]. In fact, traditional thinning methods often produce artefacts, such as bifurcations are elongations and represent original blobs and filled holes by lines instead of loops. Such anomalies incorrectly describe the structure of the source pattern and make the recovery more difficult [30, 33]. Besides, skeletonisation is considered to be highly sensitive to noise [6]. A single isolated background pixel could result in a loop being created. In reality, some researchers [33-35] exclude unreliable skeleton segments from consideration whilst others treat those as clues and examine their internal structure carefully [3, 36]. Researchers have also investigated specialized handwriting skeletonisation techniques [32, 37-41].

In [32], the skeletons were interpolated from selected points using B-Splines. The junction spline knots were shared amongst all the incoming branches before being decomposed in separate knots after a fine tuning process. Consequently, the structure of the characters was preserved. Spline knots have also been investigated in [22] where the control points were over generated equidistantly before being selectively removed to obtain the optimal set of control points. These pseudo-skeletonisation techniques were reported to be less sensitive to noise compared to traditional thinning methods.

It is [24] believed that the temporal information cannot be recovered from the skeleton using heuristic rules only. Furthermore, each clue about the motion of the writing instrument should be carefully examined in order to recover the trajectories successfully.

3.2. Contour

Another aspect for trajectory recovery is the handwriting contour. Compared to the skeleton, the handwriting contour does not frequently contain anomalies. Each point on the contour matches a position of the pen tip and is a clue for recovery.

In Plamondon and Privitera's research [6], the contour was employed to recover the trajectory of handwritten words. Initially, curvature maxima points were employed to locate ambiguous zones. Later on, two branches of a crossing were joined together based on contour curvature smoothness. The proposed system was tuned using several databases and the performance was evaluated using an untouched database consisting of 200 words, which were written by six writers. The successful ambiguous zone interpretation rate was reported to be 94% whilst the original pen tip movement recovered was 89%.

In Doermann *et al.*'s research [42], the handwriting contour has been employed to locate and recover hidden loops in three phases. Firstly, candidate contour segments are located. Secondly, candidates that a-priori do not have an elliptic shape or are not surrounded by a visible loop are discarded. Finally, blobs that meet the elliptic shape requirement are selected. In another work on loop recovery by Steinherz *et al.* [43], the contour was used to classify holes, identify hidden loops and hidden natural sub-loops.

3.3. Ambiguous Zone Detection

There are parts of the writing where the establishment of writing order is not straight forward. Many of those are occluded i.e. start/end points, crossings, and touching. They are often named ambiguities or ambiguous zones. To recover the intrinsic trajectory of the pen movement from a static image, these ambiguities must all be located and analysed.

In skeleton-based approaches, the detection of ambiguous zones often relies on the average stroke width [3, 33]. At these ambiguous zones, the distance from a skeletal point to the nearest background pixel appears to be larger than half the line width. Since line width often varies with writing instruments and writing speed [20], especially in sophisticated handwriting or signatures, handling ambiguous zones this way requires greater care.

In [6], it has been pointed out that ambiguous zones can be located using curvature maxima points of the handwriting contour. According to these researchers, curvature maxima of the contour correspond to either the overlap of two consecutive motor strokes or two distinct strokes. Similarly, Cao *et al.* [44] classified handwritten Chinese ambiguous character zones into basic and complex types using discontinuous points [45].

In another work, El Baati *et al.* [46] demonstrated that ambiguous zone detection could be performed in a simpler fashion. Their technique employs a square window sweeping through the image and counting the number of background regions parted by the handwriting simultaneously. 3 background regions correspond to a Y branch point whilst 4 means an X crossing.

3.4. Ambiguous Zone Analysis

The analysis and matching of the incoming and the outgoing parties branching from ambiguous zones can be considered the most crucial and challenging task in trajectory recovery. This operation often involves the evaluation of continuity or smoothness for each pair of lines that branch out from the ambiguous zone.

In [30], ambiguous zones in the signatures were analysed using heuristic rules. A signature is then represented by a set of critical points extracted from the recovered trajectory. From this work, a recognition rate of 97% was reported. In [33], two branches are joined if the magnitude of direction variation is smaller than a given threshold. Heuristic rules were also proposed to resolve situations where thresholding failed. Similar approach has also been employed in [47, 48]. Beside direction, stroke width and length have also been employed to evaluate continuity in [49]. Curvature based continuity functions using Kalman [50], Gaussian [6], and B-Spline fitting [51, 52] have also been investigated. Nevertheless, gray level consistency is considered helpful for this task [20].

It is reported that 95.8% of all the intersections with degree ≥ 4 have degree of 4 and 95.1% of those have degree 4 are crossing nodes [3]. This implies that proper analysis of degree 4 intersections would significantly contribute to the overall system accuracy. In [3], a neural network was employed to identify the crossing type from other types based on the tangential direction of branches. The tracing through ambiguous zones was also be assisted with the in depth analyses of the skeletal structure.

When the degree of intersection was small, it was able to list all the topologies for the crossings of a certain degree. This prior knowledge significantly assisted the analysis of the ambiguous zone as well as double traced segments [34].

4. DOUBLE TRACED WRITING AND HIDDEN LOOP ANALYSIS

Double traced writing can be defined as segment of writing which is traversed twice. Humans identify double traced and blobs easily within the context. Such information also helps to distinguish one letter from another [42].

In [36], Kato and Yasuhara provided the taxonomy of double traced writing (D-line) which includes looped (L), proper (P), and spurious (S) D-lines. The angles between branches and writing behaviour were employed to heuristically detect D-Lines in this research. Similarly, angles between branches were used to construct the weighted matrix of a general graph maximum weighted matching algorithm whose best solution would highlight the D-lines [3].

Blobs are created when the accumulated ink on the exterior of the point assembly of a ball-point pen drops intermittently to the writing surface [53]. This can be considered as another form of a double traced line whose size is usually bigger than the average trace width.

Intuitively, Abuhaiba *et al.* [54] suggested that the points lying deep inside the blob are more likely to belong to the background. The distance to the contour threshold was set to be the distance between the majority of the skeleton pixels and the contour plus 2. Explaining the modest recovery rate of 83.6%, the authors commented that both line width and blob size vary even in the same stroke that caused the introduction of spurious holes which negatively affected the performance of their recognition system. This view is also shared by Doermann *et al.* [42] who later noted the impracticality of this technique due to the high signal to noise ratio.

In their research, Doermann *et al.* [42] examined the blobs using the mutual distance measurements between the two sides of a symmetric shape. According to these researchers, a blob often resembles an ellipse. Therefore, after contour partitioning and the selection processes, only blobs that resemble elliptic shapes are considered in the shape analysis process.

Steinherz *et al.* [43] focused on the detection and resolution of the structure of handwriting loops. The researchers proposed a sophisticated algorithm which employed correspondent contour banks to determine the next course of the pen trajectory.

5. END POINTS

After all the ambiguous zones have been detected and analysed, all pairs of corresponding start point and end points need to be selected before the trajectory could be traced globally. This essential process usually includes the identification of stroke ends and hidden ends, selection of beginning points, merging of broken strokes resulted from preprocessing.

It is agreed that stroke ends' position largely depends on writing styles. For a recovery system to be successful, such knowledge should be referred. In Arabic handwriting, branch points and end point are always located to the left of the start point [46]. For a Latin right-handed writer, the writing usually begins from the top left and progresses downwards to the right [53]. Rousseau *et al.* [25] investigated the significance of knowledge about handwritten Latin letters in recovering the writing trajectory and concluded that prior knowledge has improved recognition rates.

As stroke ends may be hidden or occluded by other strokes, especially in isolated characters, the identification of the start points and the end points is not trivial and sometimes impossible. Many researchers have chosen to exclude patterns with hidden ends to simplify the problem [36, 55-57]. In Rousseau *et al.*'s research [57], as many as 9% of the isolated character samples were reported to have at least one hidden end and were removed from the experiments. The detection and analysis of end points is even more challenging in multi-stroke handwriting and signatures, which varies greatly in style and contains multiple ambiguous zones. These facts partly explain why it is observed that there has not been any attempt in the literature devoted to the automatic hidden ends identification problem [57].

6. GLOBAL RECONSTRUCTION

The final process of a handwriting trajectory recovery system is global reconstruction. This is necessary since the handwriting may consist of more than one pair of pen-down and pen-up events. Moreover, there may still be ambiguities left that cannot be analysed and only global reconstruction can enumerate all possibilities. In this process, the direction of pen movement in each segment is also established.

In their research, Bunke *et al.* [9] applied the best-first search technique on the weighted graph to find the optimal trajectory. This graph was constructed from the skeleton of characters and the costs were calculated with the consideration of the writing direction, path minimization, continuity, and direction of the loop.

In the global graph search approach, the topological structure of the handwriting image is described by a graph. The end points, junctions, touching points are represented by vertices and the lines together with curves are represented by edges. The pen trajectory is finally determined by finding the most appropriate path which traverses every edge exactly once. In Jäger's research [35, 58], each handwriting segment is represented by a vertex of a weighted graph. Two vertices are connected by an edge if the two corresponding segments join the same junction. The deviation between this pair of vertices is then assigned to this edge. The final trajectory is then determined by finding the Hamilton path which minimizes the curvature cost, which may lead to combinatorial explosion [59].

In another work using single stroke handwriting where the degree of crossings could be equal or less than four [36], Kato and Yasuhara managed to detect double-traced edges and simplified global reconstruction to a process of searching for an Eulerian cycle from a directed graph. This technique has also been employed and validated in Rousseau *et al.*'s research [57] on isolated letter trajectory recovery.

The recovery of handwriting trajectory can also be assisted with dynamic information to recover handwriting partially [18, 60, 61] or globally [26, 27, 62]. In [27], the trajectories were considered as sequences of position and direction variations. Hidden Markov Models (HMMs) were adopted to represent this information extracted from the skeletons of static signature image. The state sequences are then determined by matching the HMM to dynamic exemplars using the Viterbi algorithm [63, 64]. The optimal state sequence is finally selected by comparing the likeliness between the HMMs and its corresponding dynamic sequence exemplar.

7. PERFORMANCE EVALUATION

It is apparent that the performance of trajectory recovery techniques is subject to experimental settings. To determine the performance of a trajectory recovery system, the recovered trajectories need to be compared with the online ground truth. This can only be performed by either using the simultaneously generated on-line and off-line data as described in [62] or simulate the off-line images using the on-line data [3] and an ink-deposition model such as [65]. Morphological operators such as bicubic interpolation and anti-aliasing may be employed in latter stages to obtain smoother writing [21].

As demonstrated in the literature, the performance of some trajectory recovery techniques was determined visually and reported indirectly. Visual performance evaluation is feasible only if the number of testing samples is relatively small [36, 49]. Moreover, visual evaluation is subjective, not quantitative, and is prone to error. A few performance evaluation protocols have been proposed to overcome such limitations.

In Niels and Vuurpijl's research [66], dynamic time warping (DTW), an elastic matching technique, was employed to match the recovered trajectory and the trajectory traced by handwriting experts. In [67], Lau *et al.* replaced Kendall's distance in the Feigin and Cohen ranking analysis model by a connection metric for performance analysis. This metric takes into account stroke direction and stroke connection. In more recent research using signatures [62], Nel *et al.* constructed Hidden Markov Models for the purpose of performance evaluation from online exemplars. These HMMs are capable of identifying insertion, deletion as well as substitution errors quantitatively.

8. FINAL REMARKS

From the literature, one can conclude that trajectory based features improve the performance of offline handwriting recognition systems. Despite that, research in this area is still sparse.

A large proportion of reviewed techniques require the input patterns to satisfy one or more restrictions. Such constraints prevent these techniques from being more commonly deployed in off-line handwriting recognition systems. Table 1 presents the performance of significant trajectory recovery techniques along with their key experimental settings.

Employing a generic handwriting corpus, Plamondon and Privitera [6] obtained a success rate of 89%. Better results were reported when some constraints, such as crossing complexity, number of strokes or line width, were in place. Kato and Yasuhara [36] reported the recovery rate of 91.6% whilst Qiao *et al.* [3] reported the best recovery rate of 96%. In character recognition, Rousseau *et al.* [25] achieved the recovery rate of 93.3% when characters with unexpected models are removed from experiments. Zou and Yan [68] reported a remarkably high recovery rate of 97.6% for numerals. In loop recovery, Doermann *et al.* [42] reported the best rate of 84%.

Although there is diversity in the approaches, stroke continuity estimation is performed in many, if not all, cases. It is used to detect and analyse ambiguous zones, to detect double traced lines, loops, and blobs. However, most techniques found in the literature to date, estimate this value roughly. We strongly believe that more precise estimation would significantly improve the recovery rate. Potential continuity functions could be derived from handwriting movement models such as Lognormal [69] or Beta-elliptic [70] approaches.

With the recent interest in stroke-level off-line signature verification [71], it is expected that trajectory recovery will attract more attention from the handwriting recognition community as it deserves.

Table 1. Trajectory Recovery Research and Reported Performance

Author	Year	Material	Subject	Experimental Settings	Accuracy
Boccignon *et al.* [49]	1993	Skeleton	Characters	10,000 characters by 20 individuals	97.0%
Abuhaiba *et al.* [54]	1995	Contour	Loops	2 writers, 65 strokes, 159 blobs	83.6%
Allen and Navarro [72]	1997	Skeleton	Characters	250 dpi, 1248 characters by 12 individuals	91.6%
Zou and Yan [68]	1998	Skeleton	Numerals	NIST database	97.6%
Plamondon and Privitera [6]	1999	Contour	Handwriting	200 city names, 1390 ambiguous zones	89.0%
Lallican and Viard-Gaudin	1999	Contour	Characters	260 characters by 10 writers	90.0%
Lallican *et al.* [50]	2000	Contour	Handwriting	IRONOFF [73] corpus, 20898 training/10448 testing words by 700 individuals from	80.0%
L'Homer [34]	2000	Contour	Characters	520 characters from NIST database	90.0%
Kato and Yasuhara [36]	2000	Skeleton	Handwriting	200 dpi, 100 single stroke drawing	91.6%
Doermann *et al.* [42]	2002	Contour	Loops	1270 words by 5 individuals	84.0%
El Baati *et al.* [46]	2005	Contour	Handwriting	50 Arabic words by 2 individuals	92.0%
Lau *et al.* [74]	2005	Skeleton	Signatures	350 online training / 300 off-line testing	90.0%
Nel *et al.* [26]	2005	Skeleton	Signatures	Assisted with online references, 710 single-path signatures by 50 authors	91.5%
Rousseau *et al.* [57]	2005	Skeleton	Characters	5800 characters, single-stroked, no hidden ends	87.0%
Nefedov [75]	2006	Skeleton	Characters	50 characters whose skeletons have up to 3 junction points	97.4%
Niels and Vuupijl [66]	2006	Skeleton	Characters	UNIPEN corpus [76], 1 pixel line width, 3370 samples, samples contain skeleton artefacts are removed	86.0%
Qiao and Yasuhara [77]	2006	Skeleton	Handwriting	UNIPEN corpus, 3 pixel line width, words contain 3 and/or 4 branches intersections only	93.7%
Qiao *et al.* [3]	2006	Skeleton	Handwriting	UNIPEN corpus, 3 pixel line width, 708,881 simulated static images & 187 single-stroked offline handwriting images	96.0%
Rousseau *et al.* [25]	2006	Skeleton	Characters	5556 training/ 1852 testing multi-stroked lower case letters with unexpected models & noisy image removed	83.3%
Steinherz *et al.* [43]	2009	Contour	Loops	540 loops from IRONOFF database	80.2%

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