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Verification of dynamic curves extracted from static handwritten scripts

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ABSTRACT

Static handwritten scripts originate as images on documents and do not, by definition, contain any dynamic information. To improve the accuracy of static handwriting recognition systems, many techniques aim to estimate dynamic information from the static scripts. Mostly, the pen trajectories of the scripts are estimated. However, the efficacy of the resulting pen trajectories are rarely evaluated quantitatively. This paper proposes a protocol for the objective evaluation of automatically determined pen trajectories. A hidden Markov model is derived from a ground-truth trajectory. An estimated trajectory is then matched to the derived model. Statistics describing substitution, insertion and deletion errors are then computed from this match. The proposed algorithm is especially useful for performance comparisons between different pen trajectory estimation algorithms.

1. Introduction

Producing cursive writing or handwritten signatures on documents involves a dynamic process: the pen's position, pressure, tilt and angle are functions of time. The end result, however, is a static image with little, if any, dynamic information encoded in it. Handwriting can be either on-line or off-line. *On-line* handwriting is captured using a digitizing tablet or other electronic devices that are able to record the pen's position, pressure and tilt as it moves across the surface of the device. *Off-line* handwriting is typically recorded using a scanner to represent the document as a 2D image. On-line systems are, in general, more reliable as a means of personal identification than their off-line versions. However, off-line systems are often more economically viable and sufficiently accurate for certain applications. Off-line systems are, e.g., sufficient for the interpretation of handwritten postal addresses on envelopes and reading courtesy amounts on bank checks [1].

Since on-line systems are, in general, more accurate than their off-line counterparts, many methods have been developed to recover dynamic information from static scripts [2–30]. Most of these techniques investigate the problem of extracting the pen trajectories that created a static handwritten script, i.e., the paths that the pen followed over the document. This enables the use of on-line handwriting recognition techniques in off-line systems. Estimating the pen trajectory of a static handwritten script is, however, a challenging problem. According to Plamondon and Srihari [1]: "The success of on-line systems makes it attractiveto consider developing off-line systems that first estimate the trajectory of the writing from off-line data and then use on-line recognition algorithms. However, the difficulty of recreating the temporal data has led to few such feature extraction systems so far." Munich and Perona [31] have also shown that the pen trajectories of signatures contribute to effective on-line signature verifiers. Thus, it is concluded that the estimated pen trajectories of static scripts are particularly useful for automatic handwritten character or word recognition, or for the verification of signatures. The problem of estimating the pen trajectories of static handwritten scripts is clearly a relevant and active research topic. However, literature describing techniques to automatically evaluate the efficacy of the resulting pen trajectories quantitatively, is sparse.

In this paper, an estimated pen trajectory is compared with a ground truth in order to determine how accurate the estimated trajectory is. A synthetic example is shown in Fig. 1. A static image to unravel is shown in Fig. 1(a). Its exact dynamic equivalent, referred to as its *dynamic counterpart*, is shown in Fig. 1(b). (Note that the dynamic counterparts are unavailable in practical situations where dynamic information is extracted from static scripts. The dynamic counterparts are used, in this application, only as the ground truths to measure the efficacy of the estimated pen trajectories.) If the estimated and ground-truth trajectories are exactly aligned, i.e., if the estimated trajectory of Fig. 1(a) is identical to the ground truth in

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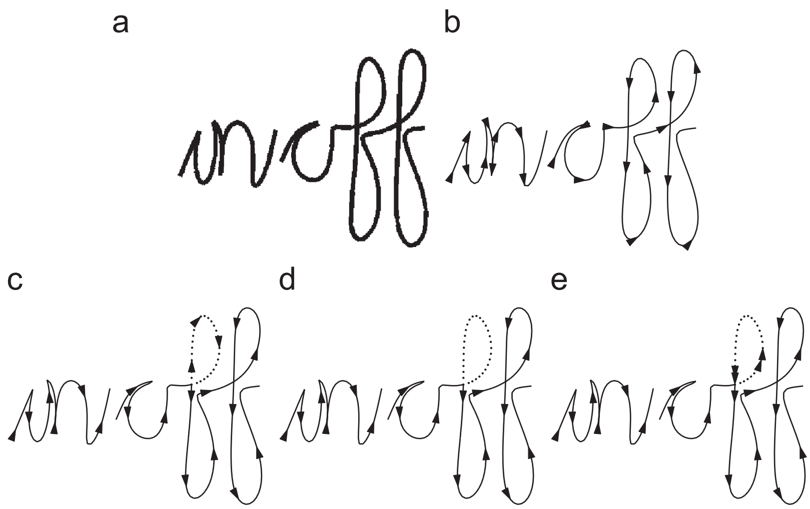

Fig. 1. (a) An image to unravel with (b) its dynamic counterpart. Typical errors (dashed lines) in the estimated trajectory include (c) substitution, (d) deletion and (e) insertion errors.

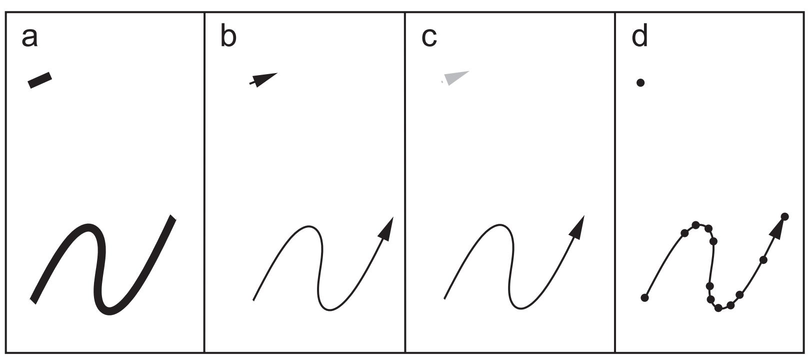

Fig. 2. (a) A static handwritten script with (b) its dynamic counterpart and (c) an estimated pen trajectory for it. (d) The points (dots) that constitute the dynamic counterpart.

Fig. 1(b), the evaluation protocol must quantify the accuracy of the estimated pen trajectory as 100%. Examples of other possible pen trajectories that can be estimated from Fig. 1(a) are depicted in Figs. 1(c)–(e).

Three error types typically occur in estimated pen trajectories, as illustrated by the dashed lines in Figs. 1(c)–(e). The first error is referred to as a *substitution* error. This error occurs when a point from the ground-truth trajectory is mapped to a mismatched point from the estimated trajectory. The erroneous point in the estimated trajectory is then called a substitution error. For example, compared to Fig. 1(b), the sequence of points that is rendered as dashed arrows in Fig. 1(c) is reversed. A point that occurs in the ground truth and not in the estimated trajectory is called a *deletion* error. For example, compared to Fig. 1(b), the dashed curve in Fig. 1(d) is omitted. A point that occurs in the estimated trajectory and not in the ground truth is called an *insertion* error. For example, compared to Fig. 1(b), the dashed line in Fig. 1(e) is repeated, as indicated by the double arrows. The erroneous points that constitute the repeated curve are therefore insertion errors. A substitution can also be described as adeletion followed by an insertion.

As illustrated above, one has to calculate a pointwise correspondence between an estimated trajectory and its ground truth. However, to establish such a pointwise comparison is surprisingly hard. Firstly, the ground-truth and estimated trajectories do not necessarily have the same number of points, making a one-to-one pointwise comparison impossible. Thus, one must typically minimize some global cost function between the two sequences to establish an optimal correspondence. However, to choose an appropriate cost function can also be problematic. If, e.g., one chooses to minimize the Euclidean distance between the ground-truth and estimated pen trajectories, inaccuracies may result between *pen-up events* (where the pen-tip is lifted from the writing surface) and *pen-down events* (where the pen-tip resumes writing). This is illustrated by a hypothetical example in Fig. 2. A static handwritten script is shown in Fig. 2(a), with its dynamic counterpart shown in Fig. 2(b). The dynamic counterpart consists of two single-path trajectories, where a trajectory between a pen-down and pen-up event is referred to as a *single-path trajectory*. An estimated pen trajectory that can be derived from Fig. 2(a) is shown in Fig. 2(c). Deletion errors occurred in the estimated trajectory, as indicated by the gray arrow in Fig. 2(c). The points that constitute the dynamic counterpart in Fig. 2(b) are rendered as black dots in Fig. 2(d). Thus, compared to Fig. 2(d), a single point was skipped in Fig. 2(c). Note that the two single-path trajectories (disconnected curves) in Fig. 2(b) have a relatively large distance between them. Thus, if one minimizes the Euclidean distance between the dynamic counterpart in Fig. 2(b) and the estimated trajectory in Fig. 2(c), a relatively large error will result due to this remote separation. This error can be misleading, since only a single point was skipped in the estimated pen trajectory. Poor compensation for such errors can therefore have a negative impact on the accuracy of the evaluation protocol.