Deliberate Practice of Handwriting: Supervision Under the Ghost of an Expert

Olivier Dikken(✉), Bibeg Limbu, and Marcus Specht

Center for Education and Learning, TU Delft, The Netherlands
o.d.f.dikken@student.tudelft.nl

Abstract. It takes considerable time, experience, and direct assistance from teachers to become a skilled writer. Handwriting fluency is one of the predictors of writing quality among students. However, students do not receive enough teacher supervision as a beginner to develop handwriting fluency in a proper manner. The "Calligraphy tutor" presented in this paper, is an application developed to assist teachers to help students learn proper handwriting fluency skills. Calligraphy tutor is designed to support deliberate practice of handwriting, in which teachers play the central role. To reduce workload of teachers, Calligraphy tutor automates repetitive actions such as providing mundane real-time feedback, while also collecting performance data from students, allowing students to practice without the presence of a teacher. The collected performance data is used by teachers to further personalise students' training.

Keywords: Psychomotor · Deliberate practice · Handwriting · Sensors

1 Introduction

Handwriting is an essential complex skill which encapsulates many other sub skills such as attention, perception and fine motor skills [10]. Handwriting impacts children's literacy skills [17]. Functional MRI techniques show that writing activates parts of the brain in children required for reading success [11]. Poor handwriting skills potentially impede the academic development of children well into their adulthood [7]. Handwriting is further advantageous into the adulthood as well. For example, in adolescents, taking notes with handwriting shows better retention and retrieval of information [16]. Therefore, it is fundamental to acquire proficiency in handwriting. However, [5] found that the students' handwriting performance is continuously degrading.

Prolonged repeated practice is required to internalise fine psychomotor skills such as handwriting, especially for children with dysgraphia [9]. Internalisation of any lower-level skills, such as in handwriting, is defined as the acquisition of fluency and automaticity of that particular skill such that no additional cognitive load is incurred during its execution. Internalisation of low-level handwriting skills, such as gestures, lead to lower cognitive demands which increases overall

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writing performance [15]. However, incorrectly internalised skills are difficult to rectify and further affect mastery of complex skills [1]. Accordingly, Bonneton-Botte et al. [2] found that teachers felt their presence was especially necessary in the early phases of handwriting learning, namely in gesture recognition. Teachers indicated, the lack of time and resources necessary [14] to supervise children in a personalised manner during gesture recognition, as one of the primary causes of incorrect internalisation of handwriting techniques. They consider it essential to provide enough teacher support to children early on during their discovery phase of learning handwriting. In this paper, we present "Calligraphy Tutor (CaT)", a handwriting teaching/learning sensor-based application which aids teachers to train students while reducing time and resources required of teachers, such that a single teacher can effectively instruct multiple students. CaT explores the following research question

1. How can we use sensors to support teachers to teach handwriting?

2 Deliberate Practice

Deliberate practice (DP) is essential for attainment and maintenance of skills such as handwriting [3]. DP is a teacher/ mentor (simply mentioned as teacher here onward) driven practice with the explicit goal of improving performance [6]. It aids students in internalising handwriting, improving their overall writing performance [15]. DP depends on the teacher's active involvement before, during, and after practice. Ericsson [6] states that expert teachers are vital for supporting the five key conditions for improving performance which lead to DP.

DP1 The teacher must define the task concretely with a clear goal and ensure that the student understands it.
DP2 Task difficulty must be barely above the students expertise level.
DP3 The practice task must be designed and performed in accordance with individualised instruction and guidance of a teacher.
DP4 The teacher should provide immediate informative and actionable feedback on each performance of the practice task which allows students to make appropriate adjustments to improve.
DP5 The students are able to "repeatedly perform the same or similar tasks".

In DP, a teacher is involved from planning a practice task for an individual student, creating it, and providing feedback during and after practice repeatedly. The teacher is also responsible for deciding when the student should progress to more complex tasks [6]. Evidently, teachers are central to the idea of DP. Hence, the CaT intends to support the teacher in classes with many students where it is not possible for him/her to provide sufficient time and resource to each student, such that students may achieve DP. To do this, the CaT implements a multitude of features which facilitate the five key conditions mentioned above. The mapping of these features with conditions (DP 1-5) are presented in Fig. 1. The teacher must create a practice task (Target trace) in the CaT environment

(DP1), and provide meta data in the form of written instructions that indicate the learning goals of the task and a list relevant of features in order of priority (DP3). The teacher then needs to replicate the target trace multiple times which generates the Expert Distribution Model (EDM, see Sect. 3.1). The student loads the created task and receives instructions on how to perform the task (DP3). While practising, live performance data from the student is used to compare his/her performance with the EDM to provide real-time actionable feedback (DP4). We define actionable feedback as simple immediate responses to incorrect actions of the student, which helps the student correct them without demanding high mental effort. To avoid information overload, this feedback is given on the mistakes in dimensions most relevant to the task which is predefined by the teacher (DP3). Feedback is provided via multiple modes (modalities) such as visual (e.g. ink color, width) or audio (e.g. a beep) and should primarily raise awareness about the student's mistakes. The student practices the task repeatedly (DP5). At the end of the session, the student submits the session, after which, writing analytics are generated, with the help of EDM, for the teacher to plan the next practice session.

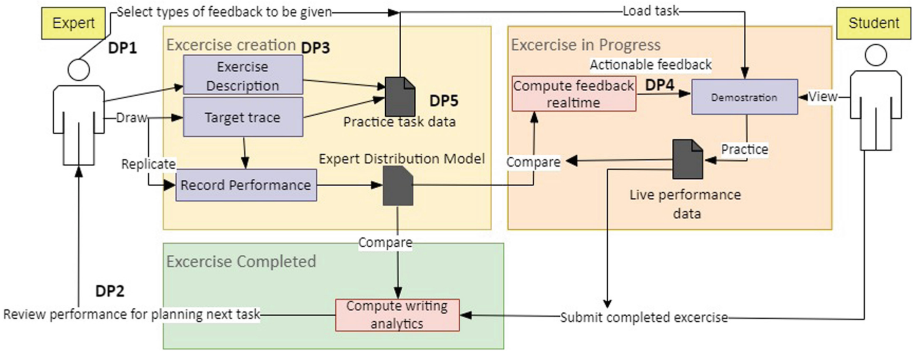


Fig. 1. Handwriting practice loop with CaT

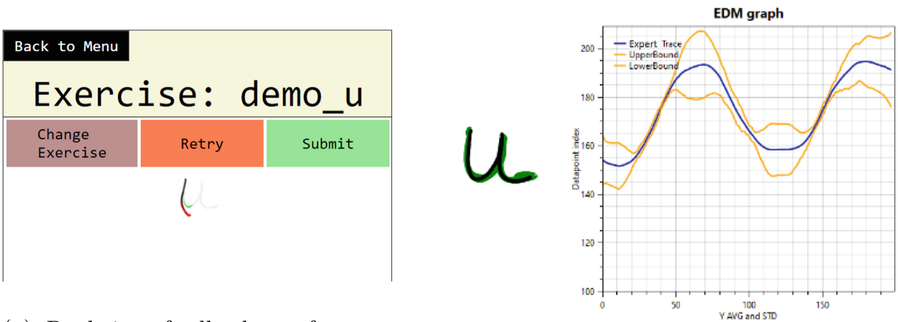
3 Calligraphy Tutor (CaT)

CaT is a Windows application built for any Microsoft Windows™PC or tablet with a digitizer and a pen support using Windows INK API. CaT uses the sensor data from the pen and the digitizer to allow a teacher to create EDMs and practice tasks. Practice task data is recorded in a temporal format. Students can load the practise task and the CaT provides feedback with the help of EDM. Feedback is provided by visual and auditory means using the PC. The CaT software is written in c# using the ASP.Net core 3.1 framework.

The CaT aims to internalise correct low-level psychomotor aspects of handwriting, in contrast to other language learning applications. Such skills are trained in early phases of handwriting learning, such as gesture recognition, where the process is more important than the end product [4]. Therefore, the CaT focuses not on retrieval of alphabets/characters but fluency and automaticity of correct psychomotor skills in the context of handwriting. This is similar to what Limbu et al. [13] pursued. The CaT takes their idea further by implementing, comparatively, more advanced algorithms for generating feedback and additional features such as writing analytics. Below we present some of the key components in the CaT, in contrast to Limbu et al. [13]'s application .

3.1 Expert Distribution Model (EDM)

Limbu et al. [13] relied on a single instance of expert performance data, i.e. their expert model relied only on one specific instance of a written trace/s as the ground truth. We define trace as individual lines that from a character. However, in handwriting, minor variations in certain properties/dimensions of the written trace/s are often acceptable. EDM dynamically accounts for these variations in the target trace/s based on the replication attempts by the teacher(s) (see Fig. 2b). These variations can be scaled to increase the tolerance as needed.



(a) Real-time feedback on features X, Y in CaT

(b) Visualisation of EDM's spatial distribution (green) & it's graph for feature Y

Fig. 2. CaT feedback elements (Color figure online)

The EDM in CaT is used as ground truth for a single exercise, and represents the teachers' performance. The EDM captures data as a list of sequential datapoints each containing several dimensions considered as important feature for handwriting as determined by Shin et al. [18] e.g. *pressure*, *direction*. For each task the EDM is annotated with meta data such as the most important features for feedback selection and specific task instructions. The EDM is used to identify errors by comparing its distribution with the student's performance. Finding errors by comparing with the EDM allows identifying the precise location and amplitude of the errors. This is in contrast to a standard machine learning approach used in [8] which involves a large labelled dataset that need to contain all errors that are to be identified, the EDM requires only a small amount of expert recordings, and can, therefore, be used in more niche contexts where large datasets are not readily available. The teacher creates an exercise by tracing the target trace/s, then recording several attempts at the exercise. The teacher should only add 'acceptable' attempts to the EDM, and in this way, the teacher can control where and which variation is allowed. The EDM is stored as a series of EDMDataPoints, which contain the average and standard deviation for each feature. To determine if the student made an error, the EDM compares each datapoint of the student's trace/s with the corresponding EDMDataPoint(s) using online dynamic time warping (O-DTW) for generating real-time feedback and DTW for batched feedback (see Sects. 3.2 and 3.3).

3.2 O-DTW for Real Time Feedback

To detect the error and measure its amplitude, the student trace/s needs to be compared, both temporally and spatially, with the corresponding part of the target trace/s which involves a form of alignment. Naive alignment methods such as the minimum euclidean distance used by Limbu et al. [13] can fail to align correctly when trace/s differ in scale, aspect ratio, rotation or when the student trace/s contains large errors in the x,y coordinates but is still a serious attempt. Automatically detecting errors in real-time is more intricate than marking the parts of the student trace/s that do not overlap with the target trace/s. Therefore, a more advanced alignment model *Online Dynamic Time Warping* is used to match student trace/s datapoints with their corresponding 'correct attempt' target trace/s datapoints in real-time. Once a student datapoint is matched with the target trace/s, the EDM's corresponding EDMDataPoint values are used to evaluate the student datapoint's accuracy per feature. To provide immediate timely actionable real-time feedback to the student (see Fig. 2a), the student-to-EDM comparison must take place several times per second, therefore the O-DTW algorithm needs to be configured to run efficiently, and uses several techniques to speed up execution, such as resampling the time series at a lower frequency, using bounds on the maximum match distance (known as *warping windows*) [20], and pruning partial paths that will lead to unpromising warping paths [19].

3.3 DTW for Batched Feedback

Batched feedback is presented and stored after an exercise is submitted, allowing the teacher to have an insight into the writing process of a student instead of only the final static output. In CaT, feedback is presented per feature, with interactive graphs that helps to map data to the context by displaying the student trace/s feature values in comparison to the EDM average and thresholds along the trace/s (see Fig. 3). Batched feedback computations do not have to run in real-time and can therefore perform alignment on sequences with higher sample rates using the complete DTW algorithm, which makes the alignment less sensitive to large handwriting mistakes (at the cost of execution time).

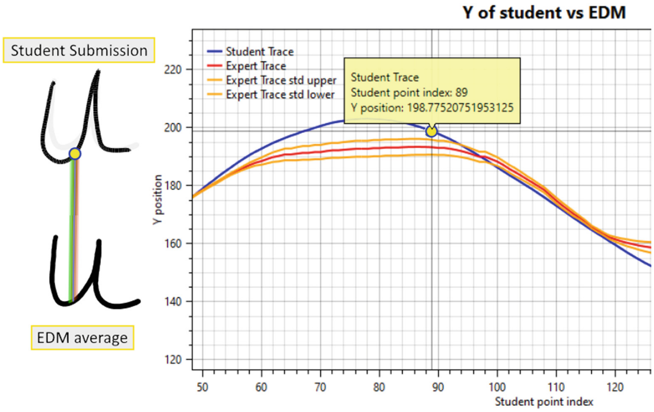


Fig. 3. Writing analytics batched feedback on feature Y in CaT

4 Conclusion and Future Work

The CaT is a teacher oriented tool for DP of handwriting during the early stages of learning. It complements the teacher by automating several aspects of handwriting teaching while still giving the teacher full jurisdiction over students' learning. The future work can include machine learning components to automate additional aspects. Furthermore, the CaT, theoretically, implements DP as originally defined by Ericsson[6]. However, other more concrete and practical frameworks such as ID4AR framework [12] which have adopted DP could potentially be an interesting future endeavour. Currently, we plan to test the current implementation of CaT for its' efficacy as a tool for teaching handwriting.

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