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Handwriting Quality Analysis of Block Letters and Cursive Words

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Abstract. *IntuiScript* is an innovative project developing a digital workbook providing feedback during the handwriting learning process for children from three to seven years old. In this context, the paper presents a method to analyse handwriting quality that responds to the expectations of the *IntuiScript* educational scenario: on-line and real time feedback for children, an automatic detection of children mistakes guiding the pedagogical progression, and a precise analysis of children writing saved to help teacher to understand children writing skills and difficulties. This paper presents first results of this project about the analysis of block letters and cursive words. Block letters are analysed with regards four different criteria *global*, *shape*, *order* and *direction* that are merged on a single score called *multi-criteria*. Cursive words are analysed as letters, bigrams and trigrams with a *global* criterion. Results shows the *multi-criteria* architecture for block letters not only improves significantly performances of the previous *global* analyser but is also able to characterise precisely mistakes of children. Finally, letters, bigrams and trigrams of cursive words give coherent scores with the deformation of cursive letters.

1. Introduction

This paper examines handwriting quality analysis as part of an innovative project, *IntuiScript*^{1,2}, which is developing a digital workbook to help teachers and children from 3-7 years old during the handwriting learning process.

The main objective of the *IntuiScript* project is to offer an advanced digital writing experience at school by using tablet and tactile digital devices (with finger touch and stylus pen, see Figure 1). This project:

- allows children to work in autonomy with online and real time feedback;
- proposes pedagogical exercises that are adapted to the level of the children based on the automatic analysis of their handwriting;
- provides precise off-line analysis of children's writing (i.e., *order*, *direction*, *shape*) to help teachers to understand children's writing skills and difficulties.

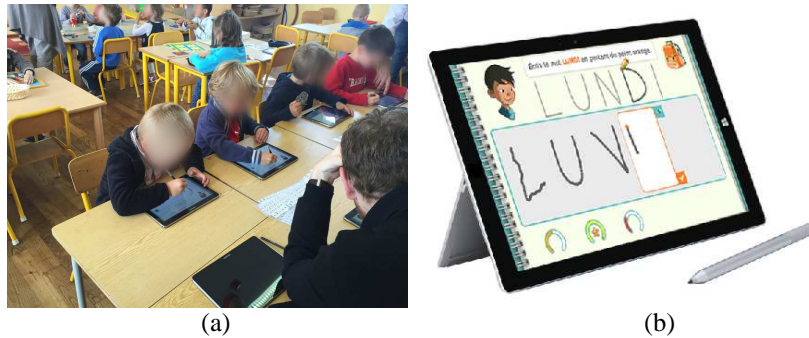


Figure 1: First in-class experiment of the *IntuiScript* project (a) with tablet tactile devices (b) example of writing the word 'Lundi' (e.g., 'Monday').

Our approach

A user-centred approach is taken that includes several cycles of conception followed by experiments. Feedback from children and teachers, related to these experiments, are used to improve the next version of the education scenario. There are two pedagogical progressions depending on the children skills: the block (single) letters where the writing process is known, and the cursive writing that they are learning. Designed by educational

¹ For more information about the project, see: <http://intuiscript.com/>

² <https://www-intuidoc.irisa.fr/en/projet-intuiscript/>

experts, and illustrated by Figure 2, the scenario for each progression is based on three hierarchical steps adapted to the skills and difficulties of each child. It is important to note that the automatic adaptation of pedagogical exercises is only possible with online handwriting analysis, such as the one presented in this paper.

- Block letters: First, based on video examples containing rules about shape, order and direction, children have to write each letter of a given word. On-line feedback with a colour scale indicator is given (see Figure 2 g, h, i, j). In the application, examples of letters correspond to dynamic animations that can be repeated as many times as children want. Then, if the system detects some incorrectly written letters, it proposes to children to work on individual letters (see Figure 2b). On-line feedback allows them to measure autonomously their progress. Finally, if the system detects that the handwriting is still incorrect, an exercise with letter primitives (e.g. horizontal/vertical/slant line, loop) is given, with the same approach as individual letters (see Figure 2c).
- Cursive writing: Children work first on an individual letter (see Figure 2d). Then, if the written production is correct, they work on bigrams and trigrams (see Figure 2e and 2f).

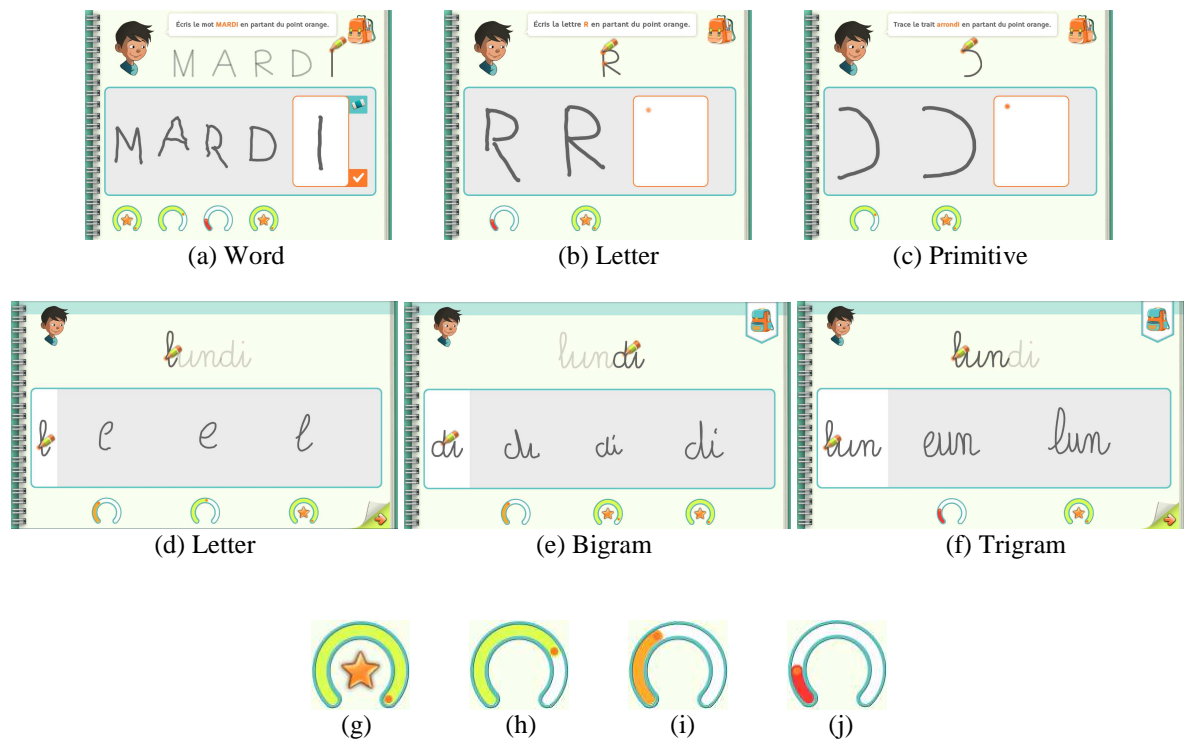


Figure 2: Hierarchical methodology that enables children to be autonomous. For block letters, the analysis is first done on letters of a word (a), then on single letters (b) and primitives (c), if required. For the cursive letter, the analysis is first done on a letter (d), then on bigrams (e) and trigrams (f). Feedback is given with a colour scale indicator drawn under each gesture with the following colouring code: very good (green with a dark star) (g), good (green) (h), average (orange) (i) and incorrect (red) (j).

Similar to other assessment tools (Falk et al., 2011; Kulesh et al., 2001; Li-Tsang et al., 2013), the proposed approach evaluates the quality of a handwritten movement with regards to a reference model using *intra-class* and *inter-class* scores (see Figure 3). For example, the *intra-class* score evaluates the similarity of a given sample U with the analysed model (i.e., U). In contrast, the *inter-class* score evaluates the confusion with other classes (i.e., how a sample U is different from another model, e.g. V). These two aspects are fundamental for handwriting analysis, which is different from handwriting recognition tools that use only the *inter-class* scores.

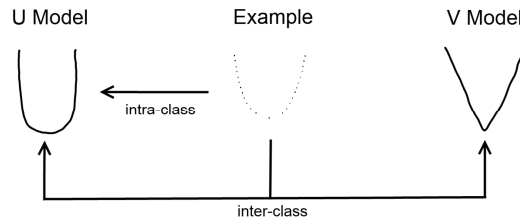


Figure 3: An Analysis of an example U. The analysis approach is based on two complementary aspects: *intra-class* (i.e. the similarity of the example with the analysed model: U) and *inter-class* (i.e. the difference with other models indicating by a confusion degree of other classes, e.g. V) scores.

2. Related Work

Writing is a fundamental skill that is necessary for learning and conveying knowledge. In the literature, handwriting quality is related to legibility and kinematics (Dinehart et al., 2015). The former corresponds to letter *shape* and its associated readiness (readability). The latter concentrates on the writing process (e.g. order, direction, fluidity) that must be efficient to be able to produce fast and legible text. More precisely, a written symbol is composed of strokes marked by the pen stopping and being lifted from the page (see Figure 4b). An *elementary stroke* is defined as a sub-stroke delimited by singularity points, and correspond to elements such as line, half circle (see Figure 4c). Thus, the writing process requires three central skills: a complete visual representation of each letter, a recognition of *elementary strokes* in letters, and the ability to reproduce a letter as a sequence of *elementary strokes* respecting the direction (Schickedanz, 1999).

There are two typical applications resulting from handwriting analysis: medical and education systems. In these two streams, a range of measures has been put forward to assess handwriting quality. For example, Guinet et al., (2010) focus on the kinematic aspect (i.e., velocity, duration, fluency, pauses) to detect handwriting pathologies. Whereas, Jolly et al., (2013) analyse handwriting velocity to identify children with developmental coordination disorder (DCD). From a developmental perspective, Accardo et al., (2013) studied handwriting kinematics of children writing on digital tablets. They considered a number of features (e.g., number of strokes per letter, peak velocities and pen lift duration) and found that handwriting is related to four important kinematic domains: velocity, spatial arrangement, automation and motor planning. Similarly, Falk et al., (2011) used five primitives – legibility, form, alignment, size and space – to quantify handwriting proficiency in children. Other research considering the production of Chinese characters has identified three types of errors: stroke production errors (i.e., stroke reversal, linking of separate strokes, broken strokes), stroke sequence errors (i.e., wrong sequencing of components) and stroke relationship errors (i.e., relative length and position; Hu et al., 2009; Tan, 2002).

In sum, approaches for medical systems (Accardo et al., 2013; Guinet et al., 2010; Jolly et al., 2013) use mainly the kinematic aspect, by opposition to educational systems (Falk et al., 2011; Hu et al., 2009) that pay more attention to legibility features and use simple kinematic features (e.g., velocity and acceleration). Legibility is often evaluated with low-level features related to the letter recognition task that makes it difficult to evaluate quantitatively the correctness of a criterion (e.g., shape in Kulesh et al., 2001). This paper presents handwriting analysers for educational systems applied to block letters and cursive words.

3. Features and Classifiers designed to recognise Handwriting Patterns

This section presents features and classifiers that are used in the analysis of block letters and cursive words. Delaye and colleagues (2013) use HBF49, which is a generic set of features designed for gesture recognition. It is composed of *dynamic* features that depends on the writing process (e.g., starting and ending positions, proportion of down-strokes trajectory, angle of the initial vector, inflexions), and *visual* features that focus on the appearance of the writing results (e.g., 2D histogram of point). This set of features captures multiple criteria: *shape*, *order*, *direction* and *global*.

A classifier is acquired with an incremental supervised algorithm (Almaksour & Anquetil, 2011; Almaksour & Anquetil, 2013) that allows the computation of *intra-class* and *inter-class* scores. In the rest of the paper, the *analysis* score refers to the fusion of these scores. These algorithms are incremental algorithms to let teachers expand models with their own drawing but, for now, this aspect is outside the scope of this paper.

4. Multi-Criteria Analysis of Block Letter Writing

The handwriting analysis of block letters is based on four criteria: *global*, *shape*, *order* and *direction*. Order and direction criteria are correct if the order and direction of *elementary strokes* (see Figure 4c) are correct. *Order* is determined by identifying the order of *median strokes* (see Figure 4d) in a gesture. *Direction* uses features based on local changes of directions. Finally, the *multi-criteria* classifier combines the results of *global*, *shape*, *order* and *direction* classifiers to give an overall result relating to all of these aspects combined.

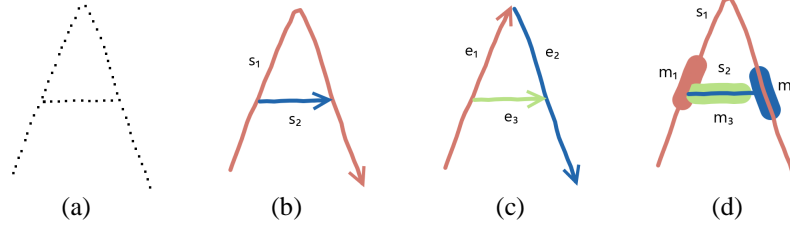


Figure 4: The original gesture from a digital device (a), and its decomposition in strokes (delimited by pen up) (b) and elementary strokes (c) with the drawing direction and order. Median strokes are represented by thicker lines in (d).

5. Analysis of Cursive writing

The analysis of cursive writing concentrates on the development of an analyser providing a *global* feedback to children because errors such as *order* and *direction* are less common with this type of writing. First, based on descending areas and singularity points (see Figure 5b), letter segments (see Figure 5c) are extracted, as in Anquetil et al (1997). Then, the *global* approach used for block letters is improved by adding features related to descending areas which are stable parts in the cursive writing.

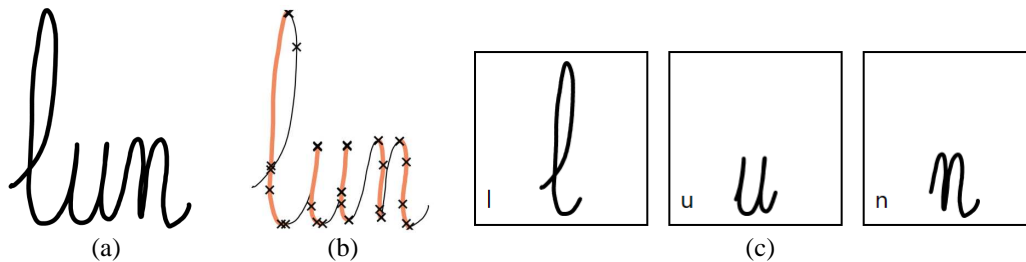


Figure 5: The original gesture (a) and the extraction of descending areas (lines in orange) and singularity points (cross) (b) that are used to extract the segmentation (c).

6. Experimentation and Results

We now present results after the first experimental trial ^{3,4} of the block letters scenario conducted in four preschools with 171 children. During a two hour session, with workshops lasting 20 minutes each, groups of 7-8 children were drawing block letters that formed words that could spell the days of the week. They received automatic feedback from the colour scale indicator (as shown in Figure 2), reflecting the correctness of the written letter.

Before discussing the qualitative and quantitative results of the handwriting analysis tool, it is important to note feedback from children about this first experimentation with tactile digital devices. In-class experiments demonstrated that children quickly get familiar with the application and tried to improve the evaluation score. Moreover, the personalised feedback allowed children to progress with autonomy at their own speed, and to stay concentrated during the whole session of 20 minutes, which is often difficult for young children. Some of them were so involved that they did not want to stop.

³ <https://vimeo.com/142233890>

⁴ <https://vimeo.com/140660028>

Figure 6 shows quantitative results with a colour scale indicator decreasing with errors of children (i.e. shape, order and direction). In this figure, arbitrary weights have been chosen for each criteria in the multi-criteria score (50% global, 30% shape, 15% order and 15% direction) but teachers can customise the weight of each criterion to give the best feedback to children depending on children skills and teacher pedagogical target for this exercise. For instance, teacher can choose to work mainly on the shape for the legibility, or to emphasise order and direction which are important skills in preparation of the cursive writing.

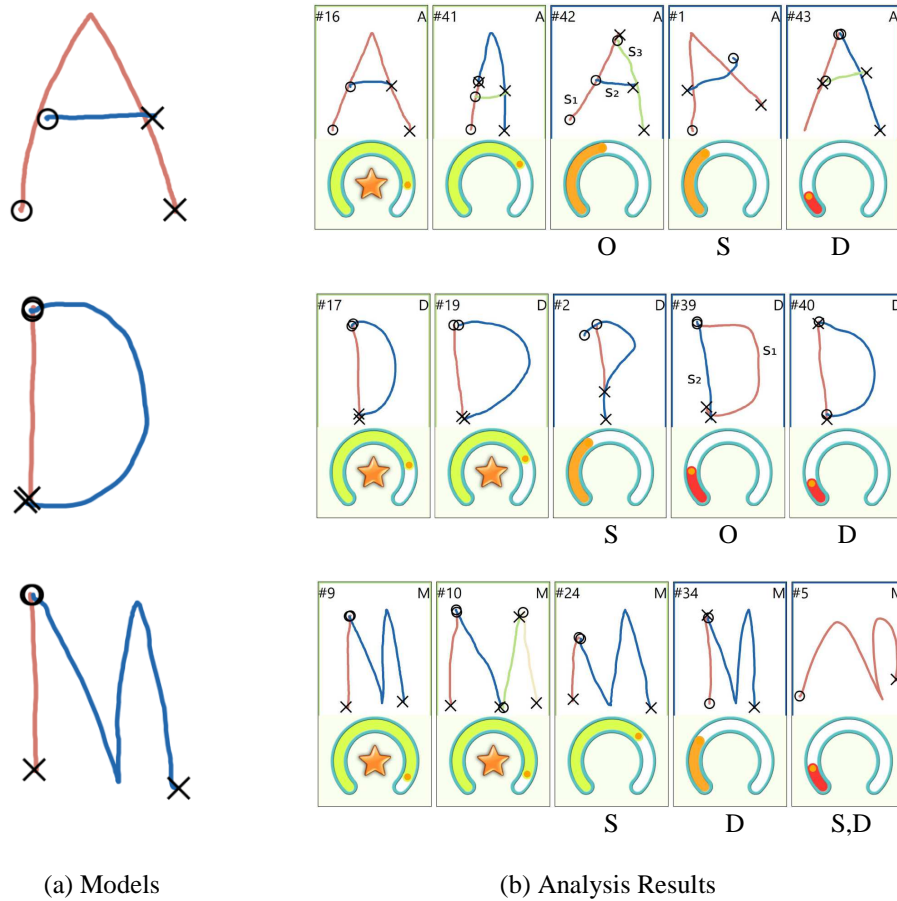
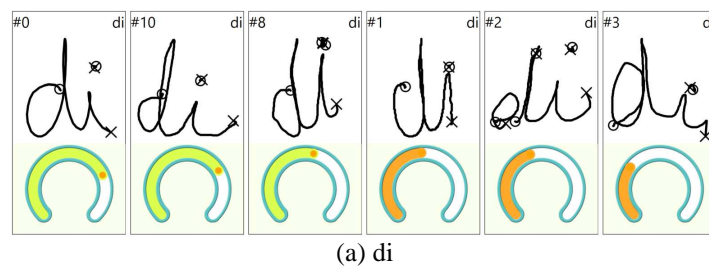
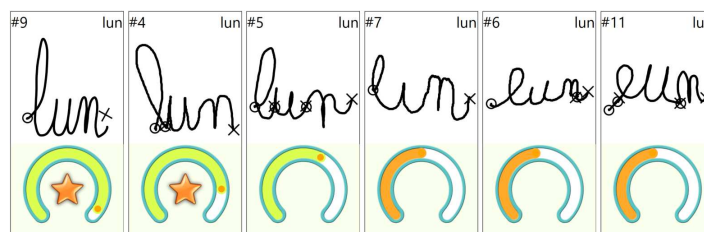


Figure 6: Qualitative results with the multi-criteria scores. (a) shows the model and (b) the analysis results and where strokes are coloured from the first to the third with red, blue and green (the begin and end of each stroke is represented respectively with a circle and a cross). S, D and O indicates respectively an error of shape, order and direction relatively to models chosen.

Experiments related to the cursive analysis are still done with 'days of the week' words. Qualitative results illustrated by Figure 7 show the classifier decreases the confidence score with the deformation of the cursive sequence.





(b) lun

Figure 7 : Qualitative results on the cursive writing.

7. Conclusion

This paper has presented a *multi-criteria* analysis of block letters and a *global* analysis of words applied in the context of the innovative project *IntuiScript*, which focuses on the development of a digital workbook to help teachers and children during the handwriting learning process. Results on a dataset collected in four preschools with 171 children have shown significant improvements compared to the *global* classifier for block letters. The independent analysis of each criteria is only given to teachers to help them during the intervention to identify the type of errors produced by children. Finally, feedback of children and teachers about the use of tactile digital devices in school has been very positive.

The next steps in *IntuiScript* project are the analysis of *fluidity*, which is a fundamental criterion to characterise cursive writing and the introduction of an *authoring* mode. More specifically, this mode will allow teachers to define their own models by firstly asking the teacher to draw letter samples and secondly by consolidating with child samples collected during the remediation to adjust the model to the teacher expectations.

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