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Handwriting learning systems: Towards an adaptation model in virtual environments

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Résumé

Handwriting learning is a complex and multi-steps process where trainees are supposed to improve several psychomotor and cognitive skills. Intelligent tutoring systems are used for non-gestural teaching and are strategy-based, whereas sensorial-feedback systems (visual, audio, haptic, ...) are widely used for gestural teaching. These approaches are reactive, improve learning performances, but do not integrate motor skill evolution through time. We discuss two challenging issues i.e. user activity analysis and adaptive guidance for handwriting learning with mixed reality systems.

L'apprentissage de l'écriture est un processus complexe impliquant différentes étapes de développement. Lors de chacune de ces étapes, l'apprenant développe différentes capacités psychomotrices et cognitives. Les systèmes tuteurs intelligents sont principalement utilisés dans le cadre de l'apprentissage de compétences non gestuelles, et sont basées sur des stratégies. Les systèmes à retours sensoriels (visuels, sonores, haptiques, ...) sont quant à eux largement utilisés dans le cadre de l'apprentissage de geste. Ces approches sont réactives, améliorent l'apprentissage, mais ne prennent pas en compte l'évolution de l'apprenant et de ses capacités au cours du temps. Nous discutons ici de deux enjeux du développement des systèmes d'apprentissage de l'écriture : l'analyse de l'activité de l'utilisateur, et le guidage adaptatif pour l'apprentissage de l'écriture en environnement mixte.

Mots clé : Sensorial feedback, adaptation, teaching in mixed reality, gestural interaction.

1. Introduction

Handwriting is a complex process, defined by van Galen [VG91] as a "multi-component task implying cognitive, psycho-motor and biophysical processes". It consists in a motor gesture, where the performer constantly analyzes and modifies his movement from his perception of his current action, and his internal representation of the "ideal" action. Furthermore, the writer not only reacts to his action, but also has a spatial and temporal representation of the shape he intends to draw. These representations imply a principle of anticipation, which means that the performer has, besides modifying in real-time his movement according to his perception, to anticipate his future movements.

Thus, learning handwriting necessitates having a cognitive representation of the shape to draw, and a perception of the different steps necessary in order to construct this shape (acceleration, angle, curve). Trainees learn handwriting through different steps, each step involving various skills (cognitive, psycho-motor or biophysical [FP67]).

To help a trainee to learn these notions, every system (be it technological or not) focuses on ways to make the trainee

explore, apprehend the letter and its components. In these systems, the trainee has to practice at some point, through observation and/or physically. For the trainee to evaluate his performance, some systems give their own evaluation (by grading and/or making the trainee's performance more explicit), when other let trainees make their own evaluation.

In this paper, we give an overview of the different ways existing systems intending to teach handwriting can help the trainee on these various notions that are exploration and evaluation. We also focus on the different senses the trainee has to use to accomplish these tasks. From pedagogical and cognitive studies conducted about motor skill and handwriting learning, we propose the idea that such systems would benefit from adapting themselves to trainees' activity.

2. State of the art

2.1. Visual exploration

Vision is a powerful yet natural sense that allows different perceptions such as colors, shapes, and spatial variables such as depth. Within the framework of learning, vision allows to create an efficient sensorimotor strategy which will make the subject able to perceive the object as a perceptual invariant and/or adjust the strategy according to the constituted invariant.

When learning handwriting, trainees will go through different phases. At the beginning of learning, movements are slow and feedback is important. Visual exploration makes trainees understand various constituents of the shape, and make a first strategy they will use to create it.

Trainees can understand spatial and temporal constituents (in other word, the dynamic) of a letter from drawings called ductus. Ductus are particularly used when learning calligraphy, showing how a letter must be constructed. Ductus give information regarding order and direction, but also speed and rhythm of writing.



Figure 1: *Typography of letter with construction order used by Bara [BGCSC04].*

Previous work has shown the effect of visual exploration in the context of learning the alphabetic principles [BGCSC04], where visual exploration on ductus, as well as sequential visual exploration have been tested. This last experiment revealed no difference between a sequential visual exploration (a black dot moving following the outlines of the letter) and a classical visual exploration (ductus, fig.1). From this statement, Bara concluded that "the most important component which can explain the efficiency of this intervention lies in the active motor exploration of letter". In the late 90's, studies (Laguna, Blandin [BLP99]) have shown that motor skill learning is better with physical practice as opposed to observational learning.

2.2. Haptic exploration

A few studies have been conducted on purely haptic exploration (without any other sense, even visual). These studies mostly show poorer results than experiments conducted on visual or visuo-haptic exploration [FKT02]. However, haptic feedback can benefit in specific situation where visual information is unreliable.

2.3. Visuo-haptic exploration

Together with visual exploration, haptic exploration makes trainees explore the letter through a physical practice. In [BGCSC04], Bara shows that adding haptic to visual exploration, by asking trainees to explore the relief letter with their fingers and run their index finger along its outline in a fixed exploratory order corresponding to its writing, improved significantly their ability to recognize letters.

In [PGBdB*07], Palluel-Germain tested another kind of visuo-haptic exploration of letter to test its impact on handwriting acquisition. In this experiment, trainees were seated in front of a table upon which the letters generated by the visuo-haptic interface were displayed on a horizontal computer screen. Children had to hold a pen attached to a force-feedback arm which attracted the pen on the correct direction if the child veered off his production on the correct trajectory, or did not produce the letter in a correct order (fig. 2).

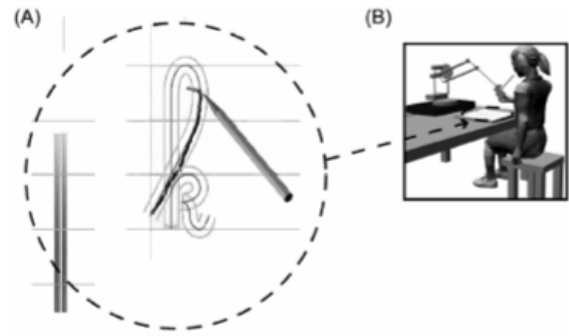


Figure 2: *The circuit game [PGBdB*07] used to test the impact of visuo-haptic exploration on handwriting learning.*

Trainees were asked to perform two exercises. At first they had to follow a road (fig. 2A), then they had to hold the pen which moved "alone" along the outline of a projected letter. Results have shown that trainees who performed these exercises, compared to another group who wrote letter on a sheet of paper (without haptic feedback), increased their handwriting ability with a greater average velocity and a smaller number of velocity peaks. However, Palluel-Germain argued that these tasks remain a copy of already-projected letter, which is not the same process as handwriting, where all the constituents of the letter have to be retrieved from memory.

Many other works have experimented the effect of visuo-haptic exploration on handwriting learning for the purposes of learning [MES07, TBL02, BPIKS10, BPK05], rehabilitating [MMN05], or transferring [BBS12] motor handwriting skills, showing promising results. In [TBL02], Teo used another force-feedback arm (6 DOFs) to teach Chinese handwriting, with the particularity that the trainee's performance display is distant from the end of the pen (fig. 3). After training, subjects exhibited improvements in accuracy and movement smoothness.

Mechanic properties of the pen can also impact learning, as proven by [BPIKS10] where increasing inertia and viscosity improved children handwriting.

2.4. Dependence to the teacher

In [BPK05], Bayart added the notion of progression to visuo-haptic exploration, with different level of guidance for the trainee. These different levels of guidance are illustrated by the freedom let to the user. In full guidance, the pen moves "alone" and the trainee only has to hold it. In partial guidance mode, forces are applied to give directions and to



Figure 3: Student learning to write the Chinese ideogram "teacher" [TBL02].

correct errors. Finally, in simple correction mode, forces are applied only when the trainee makes errors. Bayart added the notion of progression to avoid the dependence to the teacher, concern developed especially by Schmidt and Lee in the late 90's and taken again by Feygin [FKT02]. Feygin went further and split motor skill learning into three phases (fig. 4) : cognitive (where trainees understand what they are supposed to do), associative (trainees understand how to perform the task) and autonomous (when they are self-sufficient in performing the task). Any system aiming at assisting trainees (be it by teaching, tutoring or helping) must take part of the two first phases. Moreover, additional or augmented feedback on the third phase can be detrimental, since in this phase the task is supposed to be automatized, the performer using a proactive control based on his internal representation of motor act [PGBdB*07].

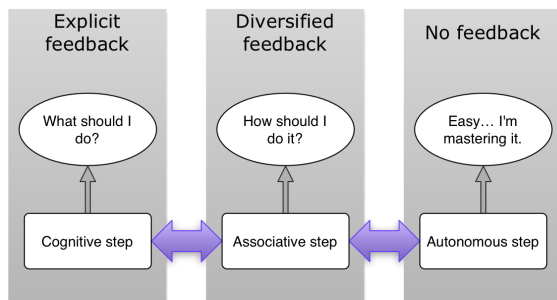


Figure 4: The three steps of handwriting learning.

Studies conducted on the dependence to the teacher issue are somehow correlated to trainees' activity. Some theories [GOT*98] describe the idea that trainees should perform on their own as much as possible. This idea does not ban haptic from any form of learning system, but recommend to let freedom to the trainee, in opposition to virtual fixture where the trainee is fully guided, which provide him from any kind of active performance.

Handwriting (and more generally motor skill) learning being a multi-steps process, a learning system should provide accurate level of guidance depending on trainees' progres-

sion through these steps. In [BPK05], the author takes the example of bicycle riding learning : At the beginning trainees need four wheels and a little push, then they can move without the push, and at the end without the extra-wheels. The same progression in the level of guidance for learning systems would remove ; or at least reduce ; the dependence to the teacher.

2.5. Evaluation

2.5.1. Handwriting recognition

Handwriting recognition has been extensively studied, essentially in order to digitize and make computer systems able to understand handwritten texts. These fields tackled the problem of handwriting recognition by using *a posteriori* recognition, meaning that the recognition is done after the text has been completed. The two possibilities are online and offline recognition [PS00]. When online recognition allows to retrieve the gesture kinematics, offline recognition only works like a test scan, and only computes the outlines. For these reasons, online recognition offers the best results.

However, these solutions for *a posteriori* recognition do not match well handwriting learning systems requirements for recognition. Handwriting learning systems need not only to recognize a character, but ideally to identify main differences between trainees' performances and a model which is seen by trainees as the objective. If it may be able to compute this kind of recognition through other paradigms such as pattern recognition, none of the studied systems have shown this ability in the evaluation. The different kinds of evaluation in current systems are developed in the following parts of this paper.

2.5.2. Quantitative evaluation

Most handwriting learning systems use quantitative evaluation through algorithms such as Hidden Markov Models or Dynamic Time Warping [KP01] to evaluate trainees' performances. The idea behind the use of these algorithms is to compute the distance from the trainee's performance to a model which is seen as an "ideal" (fig. 5).

If distance between a trainee's performance and a model can be an indicator in the evaluation of this performance (fig. 5), numerous factors cannot be evaluated by this method such as rhythm or fluidity. Furthermore, this method cannot identify any error. A trainee who wrote a "perfect" letter with one big error that makes it unreadable can theoretically obtain a better score than another trainee who wrote a readable letter with a lot of small errors.

2.5.3. Qualitative evaluation

In [TBL02], Teo proposes to add smoothness evaluation to distance measuring. To measure smoothness, Teo counts the number of crossing between two lines representing the raw path and the low-pass filtered path. Moreover, they evaluate the trainee's motion (timing of the movement at different part of the stroke) by sampling the reference and the trainee's strokes, and expressing the distance from the start to every point along the path as a function of arc length. The

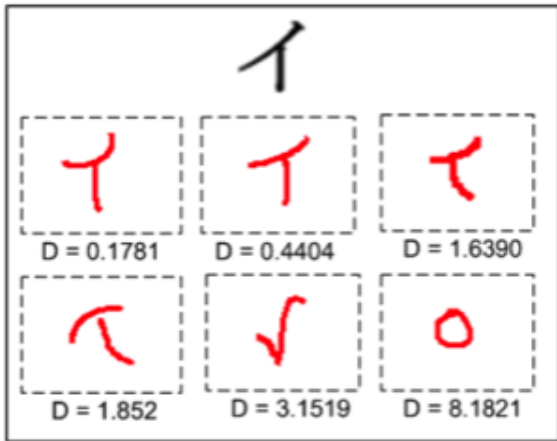


Figure 5: The DTW distance for various instances of the "i" Japanese character [MES07].

distance between the two motions is then computed from the error between the two curves. Following the same principle, they evaluate the vertical forces applied on the pen. From these results, they compute a final score using a linearly decreasing function.

By assessing various components of handwriting gesture, these methods (similar evaluations can be found in other studies [FKT02, ST05]) give a more precise evaluation of a trainees' performances. However, these methods only focus on trainees' last gesture, which may not be an exhaustive factor.

2.5.4. Cognitive evaluation

Various experiments have studied the impact of cognitive factors such as attention or focus on handwriting performances. If these studies mostly show no direct correlation between these cognitive factors and handwriting [TMWL06], they mostly rely on participants who already master handwriting gesture, which according to [FP67], mean that they passed the automation step of the learning process, and hence no longer need to give the same degree of attention as they used to need when they were in the early steps of the learning process. For these reasons, such results should, in our context, be taken with caution. Indeed, pedagogical studies on the early steps of motor skill learning show the impact of sensitive perception (which forces trainees to be focused) on learning [BLP99].

As we are taking the learning process on its whole, we cannot underestimate the impact of attention or focus on learning. Thus, we need a way to evaluate these factors. Even though no studied systems have explored this kind of evaluation, current technological solutions such as the eye-tracker should make it possible to give some precious indicators about trainees' cognitive state.

3. Challenges

Current systems improve handwriting learning. However, no study has been able to exhibit the impact of this improvement for each step of the learning process. As trainees

develop different skills in each step and thus need different feedback (modality, temporality, level of explanation), and as existing systems does not modify their behaviour accordingly, we can hypothesize that handwriting learning systems effect can benefit from an ability to adapt their behaviour to trainees. An adaptation resulting in various levels of feedback for the trainee would reduce his dependence to the learning system. Moreover, taking into account trainees cognitive state in the adaptation model might also improve the results. In this part, we discuss two areas of research which would improve handwriting learning systems impact on trainees' learning according to our hypothesis. Developing all or part of these areas, and experiment on real trainees, would allow to validate (or invalidate) the fact that handwriting learning systems would benefit from more accurate representation of trainees' activity on the one hand, and from adapting its feedback to this vision of trainees' activity on the other hand. From these results, it would be interesting to experiment a potential extension of these results to motor skill learning, and more generally to learning.

3.1. User activity analysis

From previous works studied earlier in this document, we can give an overview of main constituents of handwriting which would draw a good picture of handwriting activity (fig. 6).

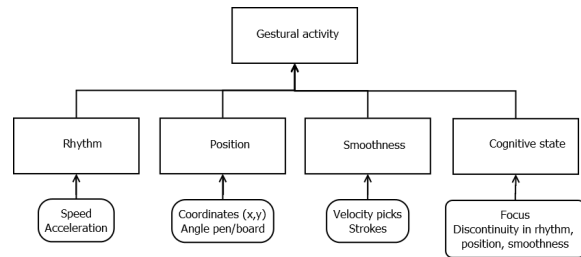


Figure 6: Constituents of handwriting activity.

3.1.1. Cognitive recognition

More than previously studied variables, we added the trainee's cognitive state, which would rely on a measure of his focus, and on a possible discontinuity in performances which might suggest that he is no longer focused on his task. Indeed, when humans can take into account the context when evaluating a performance (a child is bored or does not want to perform the task, and hence deliberately lower the quality of his performance), a system cannot. Taking into account performance discontinuities may enable systems to recognize a performance that do not show the true level of the trainee.

3.1.2. Shape recognition

If these criteria can be measured in real-time, *a posteriori* indicators such as regular errors would improve trainees' activity representation (fig. 7).



Figure 7: A regular error on the letter "a" [VS97].

3.1.3. Activity profile

From these real-time and *a posteriori* indicators, the system can build a profile of a trainee's activity. This profile should depict the trainee's level, and hence evaluate his position within the learning process illustrated in figure 4.

3.1.4. Evolution

Instead of erasing previous profile to replace it with the current, it may be interesting to keep these profiles in order to add a new evaluation criterion : the evolution of performance.

3.2. Adaptive guidance

3.2.1. Level of guidance and diversified feedback

As previously stated in this document, studies have shown that learning by practice show better results than learning by observation. In other words, active learning show better results than passive learning. However, these results are not fully applicable with handwriting learning, trainees needing elicit feedback in the first stage of the process (like the process of bicycle riding learning). For this reason, several attempts have been made to propose different levels of guidance to fit the trainee's level. These systems do not use adaptive guidance but adaptable guidance [OR97], the difference being that control on the level of guidance is held by the user (in our case the trainee, or a human teacher who helps him choose the appropriate level of guidance), not the system. Adaptability only allows systems to provide a few levels of guidance, which cannot suit trainees' needs (fig. 8).

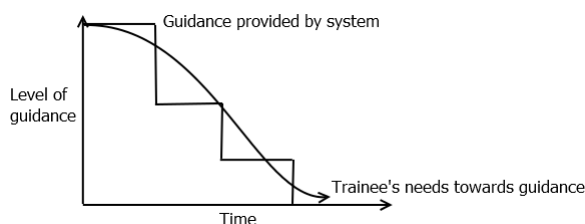


Figure 8: Difference between level of guidance provided by systems and trainees' needs.

To provide trainees with appropriate feedback throughout his learning process, a system should be able to give diversified feedback. A system can provide a diversity of feedback by modifying feedback modality (visual, visuo-haptic, audio, ...), level of explicitness (from obvious to scarcely noticeable, fig. 9) or feedback temporality (static or dynamic).

If further studies would be needed to clarify the impact of feedback modalities, explicitness and temporality on learning, it has been proven [BBS12, WW80, BPK05] that modifying these aspects of feedback make trainees improve different skills, and hence impact learning positively.

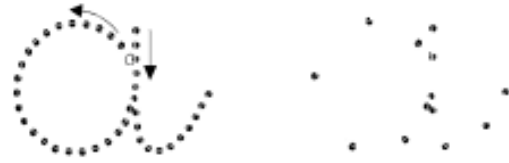


Figure 9: Two levels of explicitness for a visual guidance.

By giving control of the level of guidance to the system, adaptivity can increase the diversity of feedback provided to trainees, and hence provide more tailored guidance. However, choosing adaptivity over adaptability add a new complexity : the adaptation strategy.

3.2.2. Adaptation strategies

If adaptivity allows the system to give numerous levels of feedback, it is necessary to formulate an adaptation strategy. In other words, the system has to wonder when it has to give which level of feedback. From an accurate analysis of a trainee's activity, it becomes possible to create stages where level of guidance has to be changed (fig. 10).

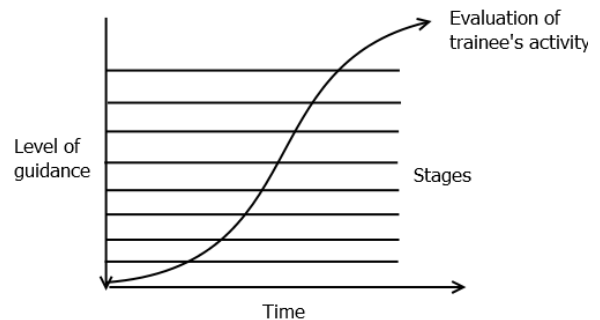


Figure 10: Level of guidance decrease depending on stages based on global evaluation of the trainee's activity.

This strategy, based on a global evaluation computed from various variables as illustrated in figure 6, might seem naive. Indeed, as trainees develop their skills (rhythm, curve, smoothness) differently, a more precise way to adapt to a trainee's activity would be to measure the evolution of these skills separately, and deciding stages accordingly (fig. 11).

In this working hypothesis, the system detects that the trainee is improving his rhythm and curve abilities. Rhythm ability improves fast, but stagnates from $t1$. However, at $t1$ the trainee is improving his ability to write curves. Hence the system chooses to stay at this stage even though rhythm is no longer improved. At $t2$, abilities for rhythm and curves both stagnates, hence the system chooses to change to the next level of guidance.

Another strategy which would make the system choose

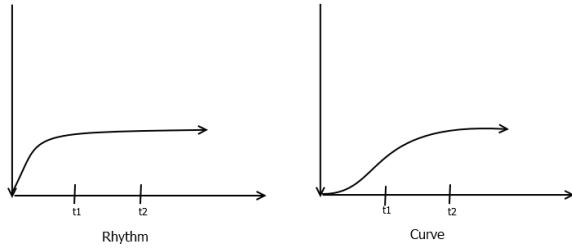


Figure 11: Analysis of trainee's rhythm and curve ability at a specific stage.

the level of guidance would be to use scenarios. However, as trainees learn very differently, it would appear to be difficult to choose the level of guidance without taking into account trainees' activity. For this reason, we did not develop this possibility here.

4. Conclusion

In this paper, we gave a state of the art regarding handwriting learning systems. If previous studies results show that these systems improve learning performances compared to traditional learning, we make the assumption that they have not reach their full potential due to a lack of levels of guidance and diversified feedback, which make trainees dependent to the teacher/system. Moreover, they do not take into account that motor skill learning processes are multi-steps, and hence trainees have different needs regarding guidance. From this assumption, we present two main challenges that would make it possible to model learning systems more tailored to trainees : activity analysis and adaptive guidance. For each of these challenges, we propose several areas of research : cognitive and errors recognition as well as dynamic activity profile to make systems have an accurate representation of the trainee's activity over time ; adaptation based on stages computed from global or local evaluations.

4.1. Future work

Based on these areas of research, we are currently working on a model which contains several sub-models for analyzing trainees' activity (gestural as well as cognitive) over time and adapting decision to this dynamic analysis in order to provide diversified feedback. Along with this model, we are creating a platform (similar to fig. 12) which will make it possible to test our model.



Figure 12: A similar platform [ST05].

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