CoWriter : Case Studies

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ABSTRACT

The CoWriter activity involes a child in an active interaction where he has to teach handwriting to a robot. Such an interaction requires to maintain the child playing as a leader. It is not obvious that a 5-7 aged child would be able to take this role and, even if he can, it is actually uncertain that he would be able to sustain his engagement during a long session (40-60 minutes). Through different case studies, this article aims to explore experimental designs and scenarios that help children to gain confidence and motivation over repetitives such long sessions. Then it introduces a measurement of how a child was satisfied by the robot's learning, and if that satisfaction was correlated to an actual improvement of robot's handwriting and also to the quality of children's own demonstrations. This measure could be a first step to automatically get information about children's understanding and self-confidence facing the activity.

Keywords

robot-supported educative activitiy, handwriting learning, learning by teaching

1. INTRODUCTION

Children suffering from difficulties in handwriting integration are more exposed to have future troubles in acquisition of other disciplines as they grow up [2]. The Cowriter activity introduces a new approach to help those children [6]. While actual successful remediations involve children in long intervention (at least 10 weeks) focused on *motor* skills [7], CoWriter is based on the *learning by teaching* paradigm and aims to repair *self-esteem* and *motivation* of the child rather than his handwriting performance.

Learning by teaching is a technique that engages students to lead an activity as teachers in order to improve the learning process. Known to produce motivational, meta-cognitive and educational benefits in a range of disciplines [11], the application of this paradigm to handwriting intervention remains, however, unexplored. One reason for this may be due to the requirement of an appropriately unskilled peer for the child to tutor: this may indeed prove difficult if the child is the lowest performer in the class. In some cases, it may be appropriate for a peer or teacher to simulate a naïve learner for the child to teach. For handwriting however, where one's skill level is visually evident, this acting is likely to be rapidly detected. This motivates the use of an artificial teachable agent which can be configured for a variety of skill levels, and for which children do not have preconceptions about its handwriting ability.

Robots have been used as teachers or social partners to promote children's learning in a range of contexts, most commonly related to language skills [5], and less often to physical skills (such as calligraphy [9]). Looking at the converse (humans *teaching* robots), Werfel notes in [13] that most of the work focuses on the robot's benefits (in terms of language [12] or physical [10] skills, for example) rather than the learning experienced by the human tutors themselves. Our work concentrates on this latter aspect: by demonstrating handwriting to a robot, we aim at improving the *child's* performance. Note that our work must be distinguished from "learning from demonstration" approaches to robots learning physical skills, as the agent we present is only simulating fine motor skills for interaction purposes.

Besides the commitment of the child into the interaction build on the "protégé effect": the teacher feels responsible for his student, commits to the student's success and possibly experiences student's failure as his own failure to teach. Teachable computer-based agents have previously been used to encourage this "protégé effect", wherein students invest more effort into learning when it is for a teachable agent than for themselves [1]. We rely on this cognitive mechanism to reinforce the child's commitment into the robot-mediated handwriting activity.

Previous experiments with CoWriter were conducted in school, involving either group of children doing the activity together [6] or children one by one but during short single session (about 10 minutes). Those studies have been conducted to evaluate the feasibility and technical soundness of the interaction system. Because of group effects and the briefness of interactions, no conclusions were possible about any actual "protégé effect". Subject children where randomly chosen in school classes and had no specific difficulties in handwriting. Therefore, it was impossible to observe any remediation of self-esteem or motivation.

We present in this article our first long-term case studies, conducted to investigate how this new activity can really impact children's self-esteem and motivation.

HRI '16 Chrischurch, New Zealand.

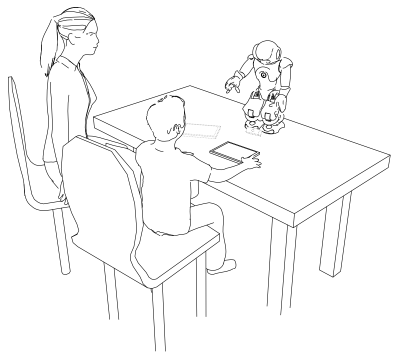


Figure 1: Our experimental setup: face-to-face interaction with a NAO robot. The robot writes on the tactile tablet, the child then corrects the robot by directly overwriting its letters on the tablet with a stylus. An adult (either a therapist or an experimenter, depending on the studies), remains next to the child to guide the work (prompting, turn taking, etc.). For some studies, a second tablet and an additional camera (lightened) are employed.

2. ACTIVITY DESCRIPTION

2.1 Interaction setup

Figure 1 illustrates our general experimental setup: a face-to-face child-robot interaction with an (autonomous) Aldebaran's NAO robot.

A tactile tablet (with a custom application) is used by both the robot and the child to write: during a typical round, the child requests the robot to write something (a single letter, a number or a full word), and pushs the tablet towards the robot, the robot writes on the tablet by gesturing the writing (but without actually physically touching the tablet), the child then pulls back the tablet, corrects the robot's attempt by writing him/herself on top or next to the robot's writing (see Figure 4), and "sends" his/her demonstration to the robot by pressing a small button on the tablet. The robot "learns" from this demonstration and tries again.

Since the child is assumed to take on the role of the teacher, we had to ensure (s)he would be able to manage by him/herself the turn-taking and the overall progression of the activity (moving to the next letter or word). In our design, the turn-taking relies on the robot prompting for feedback once it is done with its writing (simple sentences like "What do you think?"), and pressing on a small robot icon on the tablet once the child has finished correcting. In our experiments, both were easy to grasp for children.

Implementing such a system raises several challenges: first, the acquisition, analysis and learning from hand-written demonstration, which lays at the core of the our approach, necessitates the development of several algorithms for the robot to generate initial bad writing and to respond in an adequate manner, showing visible (but not too quick) writing improvements.

Then, the actual implementation on the robot requires the coordination of several modules (from performing gestures and acquiring the user's input to the high-level state machine), spread over several devices (the robot itself, one laptop and up to four tactile tablets for certain studies we conducted). We relied on ROS to ensure the synchronization and communication between these modules.

We detail each of these in the following sections.

2.2 Learning and generating letters

Since our application is about teaching a robot to write, generating (initially bad) letters and learning from demonstrations is a core aspect of the project.

The main idea is simple: allographs of letters are encoded as a sequence of 70 points in 2D-space and can be seen as vectors with 140 coordinates $(x_1, x_2, x_3, ..., y_1, y_2, y_3, ...)$. We arbitrary chose a set of allograph shapes that define the initial state of generated letters. Then, when the child provide a demonstration of a letter, the algorithm generates a new letter corresponding to the middle point between the last state and the demonstration.

The first question concerns the construction of the initial set of allographs. In previous experiments, we built a subspace based on principal composent analysis (PCA) of a standard dataset of adult 214 letters (the UJI Pen Characters 2 dataset [8]). We used the first n eigenvectors (in our experiments, $3 < n < 6$) of the covariance matrix generated from PCA. Then it was easy to create new letter shapes by choosing random coordinates close to the origin of the subspace. Each eigenvector providing the direction of a principal deformation of the allograph in human handwriting [6]. But generated "defaults" of letters were far from children deformations: this starting point produced already acceptable writings and it was too difficult for children to help the robot. Over the following studies, we explored three different ways to generate such allographs. In our first case study 3 we used homework of the child previously provided by his mother to exagerate by hand his main defaults. This way, the child was going to correct his own kind of mistakes. In the second study 4, since it was very difficult for the child to improve already recognisable allographs, we decided under the guidance of his occupational therapist to make the robot start from simple vertical stroke for all letters (round 0 on Figure 5). In the third study 5 we chose to use the middle point between a vertical stroke and normal letters as a starting point for the robot. After all those experiments, we now have a large database of children writings that could be used to generate better subspace with PCA. Recurrent neural networks (RNN) for handwriting recognition and generation [4] could also be used to generate children-like handwriting.

The second question focuses on the learning algorithm. In [6], we were projecting children's demonstrations in PCA's subspace in order to compute the middle between that point and the previous state (projected as well). Then, we just had to generate the allograph corresponding to that middle point as the new state of the robot. For the experiments introduced in this paper, we explored two other ideas: In the first study 3 we generated by PCA a subspace from a small set of allographs we drew arbitrarly. Each time the child was providing a demonstration, we added that demonstration to the small set and re-built the subspace by PCA. Then we used the same method to generate the new state from the middle point between demonstration and the last state in the subspace. From our perspective, this subspace was more adapted to the child's progression, and the sequence of tries performed by the robot looked smoother. But using metric in subspace can make the learning algorithm too slow in some cases, because consecutives projected demonstrations are sometimes too far from each other in subspace while they looks close in cartesian space. In other studies, we just used the middle point in cartesian space, in order to have a better control over the convergence of the robot tries to the demonstrations.

2.3 robotic implementation

Our system is embodied in an Aldebaran's NAO (V4 or V5, depending on the studies) humanoid robot. This choice is motivated by its approachable design [3], its size (58cm) and inherently safe structure (lightweight plastic) making it suitable for close interaction with children, its low price (making it closer to what school may afford in the coming years) and finally its ease of deployment on the field.

Robotic handwriting requires precise closed-loop control of the arm and hand motion. Because of the limited fine motor skills possible with such an affordable robot, in addition to the absence of force feedback, we have opted for *simulated handwriting*: the robot draws letters in the air, and the actual writing is displayed on a synchronised tablet.

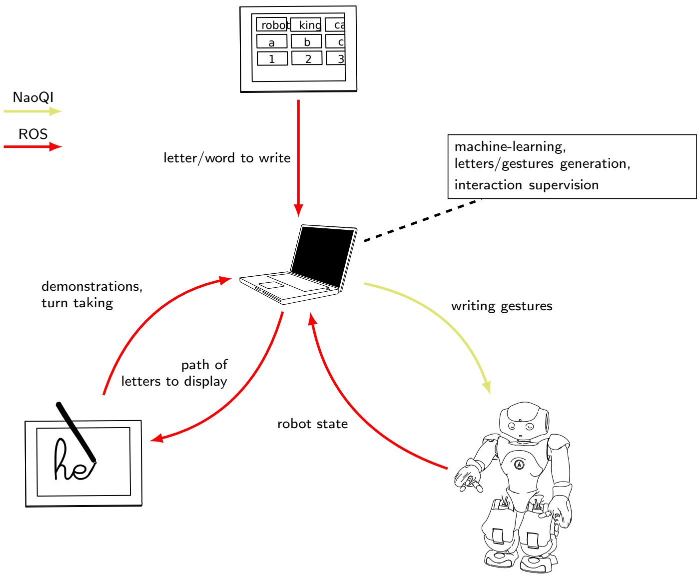


Figure 2: Overview of the system. In total, the system runs about 10 ROS nodes, distributed over the robot itself, a central laptop and Android tablets.

The overall architecture of the system (Figure 2) is therefore spread over several devices: the NAO robot itself, that we address via both a ROS API[1] and the Aldebaran-provided NaoQI API, one to four Android tablets (the main tablet is used to print the robot's letter and to acquire the children's demonstrations; more tablets have been used in some studies, either to let the child input words to be written, or for the experimenter to qualitatively annotate the interaction in a synchronized fashion), and a central laptop running the machine learning algorithms, the robot's handwriting gesture generation and high level control of the activity.

Since the system does not actually require any CPU-intensive process, the laptop can be removed and the whole logic run on the robot. Due to the relative difficulty to deploy and debug ROS nodes directly on the robot, the laptop remains however convenient during the development phase and we kept it during our experiments.

Most of the nodes are written in Python, and the whole source code of the project is available online[2]

3. CASE STUDY 1: DIEGO

3.1 Context

Diego is a five years old child. Her mother told us he had difficulties learning to write at school, particulary in drawing cursive letters. Before experiments, she provided us with a homework of Diego to show explicitly his handwriting level.

From our perspective, Diego is shy and quiet. He suffers from a poor self-esteem much more than any actual trouble in writing.

3.2 Questions

The CoWriter activity needs a child engaged as interaction leader. In this study we consider the problem of long-term interactions: is it possible to sustain this engagement over several one-hour sessions?

3.3 Experimental settings

The experiment took place in our laboratory. Our goal was to provide Diego with an environment that would enable him to sustain engagement over four sessions of one hour, one session per week. We decided to introduce an appealing scenario that justified the activity to the child where a robot wants to learn handwriting. We used two Nao robots: a blue one (called Mimi) and an orange one (called Clem). Mimi was away for a scientific mission, and the two robots had to communicate by mails. But they decided to do it "like humans", with handwritten messages. While Mimi was good in handwriting, Clem had strong difficulties and needed the help of Diego.

The mission of Mimi consisted in the exploration of a mysterious hidden base. Each week, just before the session, it was sending a postal mail contening a picture, a curious object it found and a few handwritten words about its discoveries. The picture was representing itself exploring a dark room of the hidden base (that was actually our laboratory's workshop). The objects were 3D printed. In fact, there where puzzle pieces of a small 3D model of Nao robot but seen separately, it was not easy to guess it.

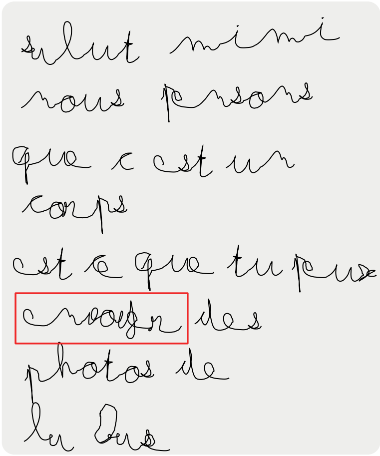
During the three first sessions, Clem (the other robot) was waiting for Diego with the received mail. It let Diego take a look at the picture and the object, and then it asked him to read the message. Finaly, Diego figured out a response and helped the robot to write it.

The fourth and last session was set as a test: Mimi, the "explorer" robot, had come back from its mission and it actually challenged Clem in front of Diego: *"I don't believe you wrote yourself these nice letters that I received! Prove it to me by writing something in front of me!"* This situation was meant to evidence the protégé effect: by judging the other robot's handwriting, Mimi would implicitly judge Diego's skills as teacher, and in turn, Diego's handwriting.

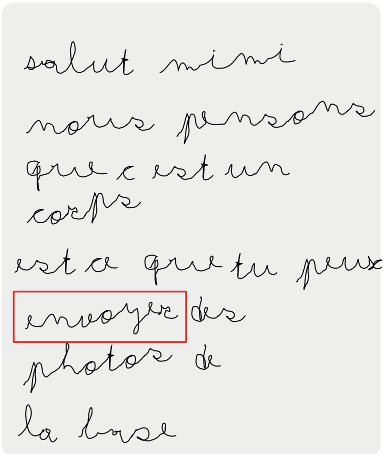
To complement the intrinsic motivation of helping a robot to communicate with another one, we gradually increased

[1]The ROS stack for NAO is available at `http://wiki.ros.org/nao_robot`.

[2]The primary repository is `https://github.com/chili-epfl/cowriter_letter_learning`.



(a) Initial letter, generated by the robot



(b) Final letter, after training with Vincent

Figure 3: (French) text generated by the robot, before and after a one hour long interaction session with the child. As an example, the red box highlights the changes on the word "envoyer".

the complexity of Diego's task to keep it challenging and interesting (first week: demonstration of single letters; second week: short words; third week: a full message – Figure 3).

Diego had to tell the robot what to write with small plastic letters (visible behind the robot on Figure 4). A third person was here to send the formed word to the robot via the computer.

3.4 Results

Overall, Vincent provided 154 demonstrations to the robot, and he remained actively engaged over the four weeks. The story was well accepted by Vincent and he seriously engaged into the game. After the first week, he showed good confidence to play with the robot and he built affective bonds with the robot over the course of the study, as evidenced by some cries on the last session, and several letters sent by him to the robot *after* the end of the study (one of them 4 months later) to get news. This represents a promising initial result: we can effectively keep a child engaged with the

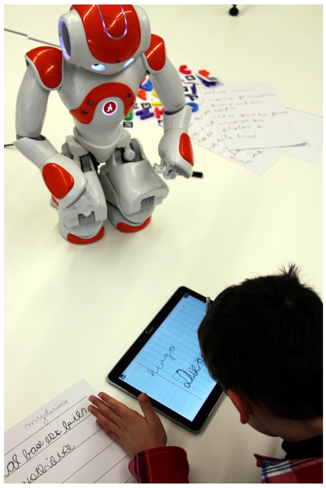


Figure 4: Vincent correcting NAO's attempt by rewriting the whole word. Empty boxes are drawn on the screen to serve as template for the child and to make word segmentation more robust.

robot for a relatively long period of time (about 5 hours).

No conclusion can be drawn in terms of actual handwriting remediation: we did not design this study to formally assess possible improvements.

However, as pictured on Figure 3, Vincent was able to significantly improve the robot's skill, and he acknowledged that he had been able to help the robot: in that regard, Vincent convinced himself that he was "good enough" at writing to help someone else, and this is likely to have positively impacted his self-esteem.

4. CASE STUDY 2 : HENRY

4.1 Context

Henry, 5.5 years old child, is under the care of an occupational therapist. He has been diagnosed with visuo-constructive deficits. As an effect in writing activities, he was frequently performing random attempts and then was comparing with the provided template. What is more, Henry is restless and careless: he rarely pays attention to advice, even to what he is doing when he is currently drawing, and he is quickly shifting his attention from one activity to another.

Henry was working on number's allographs with his therapist. During a prior meeting, the therapist provided us with a sequence of numbers written by Henry **??**. Henry was sometime drawing horizontally-inverted allographs, mainly for "5".

4.2 Questions

This study focuses on technical adaptations of the CoWriter activity for a child diagnosed with real writing deficits. Our objective is to investigate small modifications of the activity adapted to the troubles of Henry (visuo-constructive deficits and inattention) in order to maintain him focused on the activity during forty-minutes sessions, and to make the robot evidently learning from his demonstrations.

4.3 Experimental settings

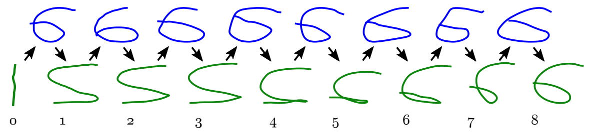


Figure 5: Demonstrations provided by Thomas for the number "6" (top row) and corresponding shapes generated by the robot. After eight demonstrations, Thomas decided that the robot's "6" was good enough, and went to another character: in that respect, he was the one leading the learning process of the robot.

The experiment was conducted in the therapist's surgery (four sessions spanning over 5 weeks). We assumed that a scenario like the one we used for Vincent was no longer relevant with Henry. We just introduced the robot and quickly said that it was seeking help to train for a robot handwriting contest.

In order to integrate our work with that of the therapist, we decided to adapt the CoWriter activity to teach numbers to the robot.

Since Henry was frequently drawing horizontally-inverted numbers, or even unrecognizable allographs, the learning algorithm of the robot was converging to meaningless scrawls. To fix this problem, we programmed the robot to refuse allographs that were too distant to a reference with a threshold we arbitrary fixed. In that way, the child was forced to take care on what he was providing to the robot as demonstration.

According to the therapist, it was easier for Henry to memorize the way to draw a number if it was always done is the same order, *e.g.* if the "5" was always drawn from the top-right tip down to bottom. Therefore we programmed the robot to refuse as well a good allograph drawn in a wrong order. But in order to reassure Henry about the right final allograph's shape, we made the robot able to recognize such a drawing, and, when it occured, to tell the child something like: *"Oh, this is exactly the shape of the number I want to learn, but can you show me how to draw it in the opposite order?"*

Also, to make the robot's progresses evident, we modified the initialization step of the learning algorithm to start with a roughly vertical stroke instead of a deformed number (round 0 on Figure 5).

In this setup, we added a second tablet with one button per number. It was used by the child to chose a new number to teach to the robot. It also provided the possiblity to enter letters or words, and to switch to another activity (the robot telling a story).

4.4 Results

Despite his inattention, Henry was able to remain engaged in the activity during more than forty minutes in each session. In total, 55 allographs out of 82 provided by the child as demonstration were acceptable by the robot (with a progressive improvement from 13 out of 28 in the first session up to 26 out of 29 in the last session).

As soon as Thomas understood that the robot was only accepting well-formed allographs, he started to focus on it and he would typically draw 5 or 6 times the number before actually sending to the robot (the tablet lets children clear their drawing and try again before sending it to the robot).

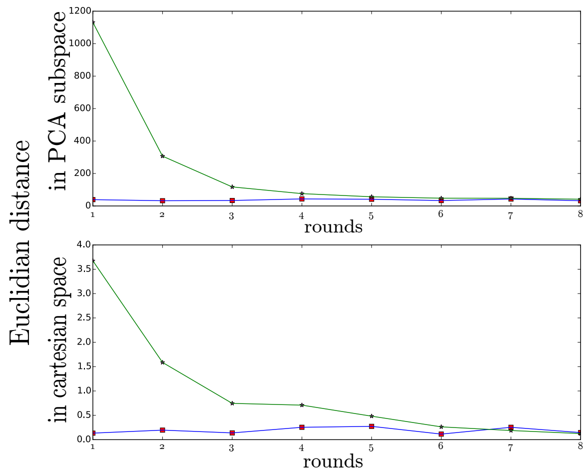


Figure 6: Two metrics to assess the handwriting progresses: Euclidian distance in the subspace of the number dataset (top figure) or in cartesian space (bottom figure). Green lines represent the robot performance, blue lines performance of the child. The round IDs correspond to the demonstrations pictured on Figure ??.

According to the therapist, it was the first time that Thomas would correct himself in such a way, explicitly having to reflect on how *another agent* (the robot) would interpret and understand his writing. Figure 7 shows how he gradually improved his demonstrations for some numbers, according to the metric we used to make the robot accept/refuse trials.

Since the robot's handwriting started from a simple primitive (a stroke), each time Thomas succeeded to have his demonstration accepted by it, the robot's improvement was clearly visible (as measured in Figure 6). This led to a self-rewarding situation that effectively supported Thomas' engagement.

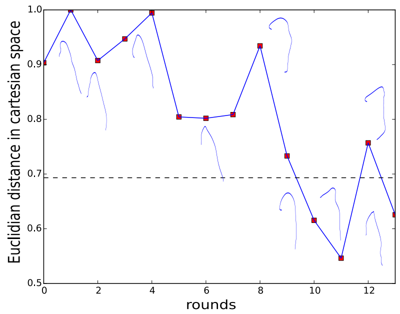
5. AUTOMATIC STUDIES

5.1 Context

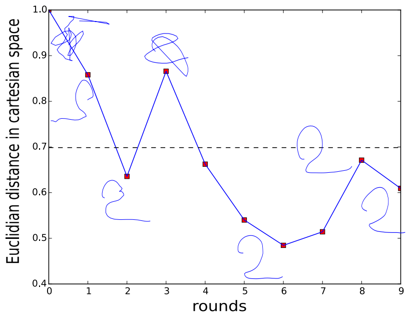
The previous studies were adapted to children : we used a special design for each case in order to sustain the child's engagement in the study. This time, we conducted case studies with eight children trought a unique design. Those children have in common difficulties to learn cursive writing but the natures and intensities of those troubles are radically different from one child to another. Valentine (7 years old), Alexandre (6.5) and Jonathan (7) are under the care of an occupational therapist. Enzo (8) and Matenzo (7) are repeating their school year because of writing. Mona (6) and Adele (8) are bottom of their respective classes in writing activities. Nathan (7) is under the care of a neurologist, and has been diagnosed with specific language impairment. All of those children are expected, given their school level, to have in mind the allographs of cursive letters.

5.2 Questions

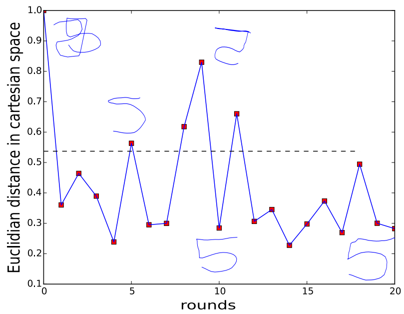
The main purpose of this study is to test the ergonomy of CoWriter. As we introduce the robot, we do not provide children with any scenario and give to them minimal explanations. Then we see how easily they take the role of the teacher and how seriously they try to help the robot.



(a) number 1



(b) number 2



(c) number 5

Figure 7: Improvement of Henry's demonstrations for some numbers: a) drawing the allograph of the number 1, b) the number 2 and c) the number 5. Henry progressively took care of the demonstrations he was providing to the robot for those numbers. We used for this figure the same metric than the one used for the acceptance algorithm. Distances are normalized with respect to the biggest value. The dashed line correspond to the threshold of robot's acceptance.

5.3 Experimental settings

This experiment took place in the coffee room of a therapists shared surgery in Normandy, France. Over two weeks, each child came three time for one-hour session, except Adele and Mona who did just one session. A facilitator was here just to explain the rules of the game and tablet usage. As for Henry, the child had two tablets : one to choose a word (or a single letter) to teach, and one used by both the child and the robot to write. Sometimes, if the child asked for, we provided him with allograph's template.

The starting point of the robot's writing was the same for all children: we used middle point between simple vertical strokes and letters. For this study, we wanted the robot to be only influenced by the demonstrations provided by the child, so we did not project allographs in a subspace. The generated trials of the robot were directly the middle way between demonstration and last state in cartesian space.

The robot was programmed to accept all demonstrations, giving to the child the full responsability of the teaching leader.

We added two buttons on the tablet interface. a green one with a thumb up, and a red one with a thumb down. Those buttons could be used by children to evaluate the robot (the green one was for rewards while the red one was for punishment). This way, we could mesure the perception of the robot by the child: the more the child used evaluation buttons, the more he was playing the teacher, judging the robot instead of himself. It becomes possible to estimate if a child is playing seriously given correlation between his evaluation and robot's actual progression.

5.4 Results

All children maintained their engagement during the full sessions. They provided on average 42 demonstrations per session. All children used evaluation buttons and had preference to reward the robot (at the end, 99 rewards were accorded to the robot for 33 punishments).

Since sessions took place over only two weeks, we did not studied possible handwriting remediation in children.

We focused on correlation between the children's evaluations and the robot's progression. We estimated the robot's progression as the difference between a starting score (score of the first robot's try when children have chosen a new word/letter to work on) and the current robot's score (after being taught by the child). that score is given by the average of euclidian distance between robot's try and a reference allograph over all letters of the word. Those references for letter allographs where drawn by us beforehand, taking inspiration in education.com cursive letters templates (`http://www.education.com/slideshow/cursive-handwriting-z/`). Let P_i be the estimated progression of the robot at time i. Of course, if the child chose to switch to a new word at time j , we have $P_j = 0$ and clearly $P_0 = 0$. To mesure whether the fact that the child was rewarding the robot when it was progressing was significant or not, we generated 10000 times the same number of reward/punishment but accorded at random times. Let R_i^n be the n^{th} generated evalutation at time i ($R_i^n = 0$ if no evaluation occured at time i , $R_i^n = 1$ if a reward occured at time i and $R_i^n = -1$ if a punishment occured at time i), and $\overline{R}_i$ be the actual evaluation at time i. For each n^{th} generated sequence of

child	demo	rew	pun	p(robot)	p(child)
valentine	127	24	6	2.4e-03	5.5e-02
enzo	223	20	9	1.7e-01	3.5e-01
matenzo	131	10	3	3.8e-03	7.9e-03
jonathan	98	10	5	1.5e-01	3.8e-01
nathan	115	16	4	5.3e-04	2.7e-03
alexandre	83	10	3	3.1e-02	6.0e-01
adele	35	4	2	5.0e-02	3.7e-02
mona	40	5	1	5.4e-01	2.0e-01

Table 1: results of evaluations. demo: number of demonstrations provided by the child over all session. rew: number of rewards accorded by the child. pun: number of punishments. p(robot): are the evaluations significantly corresponding to the progression of the robot ? p(child): are the evaluations significantly corresponding to the child's own progression ?

evaluation, we compute a score of evaluation:

$$S^n = \sum_i R_i^n P_i$$

Then we can estimate the p-value p of the actual score:

$$\overline{S} = \sum_i \overline{R}_i P_i$$

given the distribution of the generated scores $\left(S^n\right)_n$, assumed to be gaussian:

$$p(\overline{S}) = \mathbb{P}\left[X > \overline{S}\right] = 1 - \phi\left(\frac{\overline{S} - \mu}{\sigma}\right)$$

where ϕ denotes the cumulative distribution function of the standard normal distribution, μ the mean and σ the deviation of the generated scores $\left(S^n\right)_n$. As a result, we found that 5 of the 8 children obtained a score of evaluation significantly hight ($p(\overline{S}) < 0.05$). We reported score of evaluation p-values of each child in the second-to-last column of Table 1.

Then, we also studied correlation between children's evaluations and their own progression. We did exactly the same analysis, using distances between children demonstrations and reference allographs to compute children progressions. Finaly, 3 of those 5 children that played "seriously" obtained score of evaluation of their own progression significantly hights (last column of Table 1). For those last children, it seems that the robot was reflecting their own performances, and while they were judging the robot positively (three times more rewards than punishments) they were actually evaluating themselves.

6. CONCLUSION

Those studies provide the first results of long-term experiments with CoWriter activity performed by one child at the time.

We introduced some adaptations of the interaction design and the learning algorithm that succeeded in keeping children engaged during repetitive long sessions ($\sim$ 45 minutes, 3 or 4 times). Such design of possible long-term interaction provides opportunity to study and improve actual impact of human-robot activities as education tools.

The fact that a child with real difficulties in handwriting can easily understand the activity and feel that the robot actually learns from his demonstrations reveals that CoWriter could have a positive therapeutic impact.

The evaluation of the robot by the child provided information about his understanding of the activity and about how much he was satisfied by the learning process (both the robot's ability to learn and the child's own ability to teach). We believe that this information could be taken into account by the robot in order to improve the quality of the interaction. As an example, it could be used at two levels : (1) it is possible to detect if the child is playing seriously or not (a non-serious child may provide unrecognizable drawings and gives good grades to the robot while its level decreases), or if the child did not understand the activity (if he never uses the evaluation buttons and spends a lot of time to give a response). (2) We can simply reinforce the learnt allograph when the robot receives a good evaluation, or make it forget the allograph when it receives a bad evaluation.

Acknowledgments

This research was partially supported by the Fundação para a Ciência e a Tecnologia (FCT) with reference UID/CEC/50021/2013, and by the Swiss National Science Foundation through the National Centre of Competence in Research Robotics.

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