Building successful long child-robot interactions in a learning context

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ABSTRACT

The CoWriter activity involves a child in a rich and complex interaction where he has to teach handwriting to a robot. The robot must convince the child it needs his help and it actually learns from his lessons. To keep the child engaged, the robot must learn at the right rate, not too fast otherwise the kid will have no opportunity for improving his skills and not too slow otherwise he may loose trust in his ability to improve the robot' skills. We tested this approach in real pedagogic/therapeutic contexts with children in difficulty over repetitive long sessions (40-60 min). Through 3 different case studies, we explored and refined experimental designs and algorithms in order to fit troubles of each child and to promote their motivation and self-confidence. We report positive observations, suggesting commitment of children to help the robot, and their comprehension that they were good enough to be teachers, while they came with a feeling of handicap in handwriting.

1. INTRODUCTION

Children facing difficulties in handwriting integration are more exposed to troubles during the acquisition of other disciplines as they grow up [5]. The CoWriter activity introduces a new approach to help those children [10]. While common successful interventions involve children in long intervention (at least 10 weeks) focused on *motor* skills [12], CoWriter is based on *learning by teaching* paradigm and aims to repair self-confidence and motivation of the child rather than his handwriting performance alone.

Learning by teaching is a technique that engages students to conduct the activity in the role of the teachers in order to support their learning process. This paradigm is known to produce motivational, meta-cognitive and educational benefits in a range of disciplines [22]. The CoWriter project is the first application of learning by teaching approach to handwriting.

The effectiveness of our learning by teaching activity is 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", where students invest more effort into learning when it is for the benefit of a teachable agent than for themselves [4]. We rely on this cognitive mechanism to reinforce the child's commitment into the robot-mediated handwriting activity.

In this study, we assume that the key of such a relationship between the child and the robot relies on the credibility of the robot: The more the robot convinces the child that it is a beginner in handwriting who needs help – building the "protégé effect"– the better the child will engage in the interaction. Two important technical aspects of credibility are: how to generate the initial state of the robot, and how to design its learning behavior. In our previous work [11], we used a limited approach in which letters had to be written as a single stroke (no pen lifting) and that covered typical mistakes of adults extracted from an handwritten letters database. Experiments with CoWriter were conducted in school, involving either group of children doing the activity together or children in short individual sessions.

These studies have been conducted to evaluate the feasibility and technical soundness of the interaction system. Because of the group effect and the briefness of interactions, no conclusions were reached about any positive effect of the interaction. Subject children where randomly chosen in school classes and had no specific difficulties in handwriting. This made it impossible to observe any remediation of self-esteem or motivation.

In this paper, we explore different algorithmic and staging approaches built on the system presented in [11] in order to figure out intricate aspects of long child-robot interactions in a pedagogical context. We solved previous technical limitations of robot's letter learning and generation, and we introduce new algorithmic approaches that make robot's behaviour more convincing. Through three experiments, we involved children with real difficulties or low self-esteem in repeated long sessions (four times about one hour). We used different measures, both qualitative and quantitative, to express the impact of those interaction with the CoWriter robot on the child.

This article consists of four sections. In the first section we give technical details of our setup, such as how are connected the different modules together and which algorithms are used to learn and generate robot's letters. The following three parts report our three experiments and results. Two case studies specifically designed to be adapted to one child;

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one introduces a general design conducted with 8 children separately.

2. RELATED WORK

Concerning learning non-physical skills, the protégé effect have been used in the past by computer-based agents [4]. Robots maintain better long-term relationship [14] and contribute to obtain more learning gains [17] than with screen-based agents in pedagogical interactions. Specifically, when learning physical skills, robotic partners have been showed to increase users' compliance with the tasks [1].

Many studies have been conduced with language skills acquisition [9], less often involving physical skills (such as calligraphy [19]). Regarding *learning by teaching* paradigm with robots, Werfel notes in [25] that studies tend to focus on the ability of the robots to learn (in terms of language [23] or physical [20] skills, for example) rather than the beneficial impact on the teaching for the human. To contrary, our work minimized the robot's skills while we concentrate on the possible improvement of children self-confidence and motivation promoted by the behaviour of the robot.

The usage of tutor robots in educative activities with children is a sensible point. A bad choice of the robot's behaviour can have negative impacts on the learning [13], that are consequent in long-term interactions [15]. Peer robot partners seems more efficient than tutor [26], but no such study relates advantages of learning by teaching a robot. However, Tanaka and Matsuzoe [24] explored this paradigm with a Nao robot learning vocabulary from children, and Chandra [3] used a peer robot leading a learning by teaching activity performed by two children.

A remaining difficulty in Child-Robot-Interaction concerns the evaluation of the interaction. Using questionnaires with children can lead to contradictions between the actual behaviour of the child during interaction and his answers during the interview [16]. One reason is that children have the tendency to try to please the experimenter, rather than answer truthfully to survey questions [2]. Various metrics can be used to describe the behavioural aspects of the interaction (duration of interaction, proximity ...) and learning gains (pre/post tests), but it is much harder to obtain measure of psychological impacts without a very large sample size providing significant results [2].

Measurement of the children engagement must be based on a rigorous model. O'Brien and Toms [21] provided such a framework and listed different attributes that can provide information about the engagement. In our context of Human-Robot-Interaction, we can make distinction between tree kind of engagement : social engagement, task engagement and social-task engagement [6]. Along this paper, we focus on the persistence of the "protégé effect": we aim to play with the children's perception of the robot in order to create motivation. In that way, we base our observations and results on metrics of social-task engagement.

3. EXPERIMENTS DESIGN

3.1 Interaction overview

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: in each turn, the child requests the robot to write something (a single letter, a number or a full word), and pushes 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 himself on top or next to the robot's writing (see Figure 3), and "sends" his demonstration to the robot by pressing a small button on the tablet. The robot learns from this demonstration and tries again.

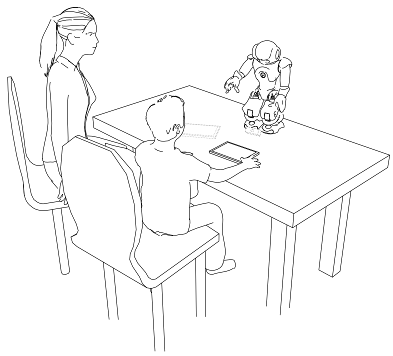


Figure 1: Our experimental setup: face-to-face interaction with a NAO robot. The robot writes on the tactile tablet, the child then corrects the robot by directly overwriting its letters on the tablet with a stylus. An adult (either a therapist or an experimenter, depending on the studies), remains next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

Since the child is assumed to take on the role of the teacher, we had to ensure he would be able to manage by himself 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. We found that both approaches were easy to grasp for children.

3.2 Generating and learning letters

Since our approach is based on teaching a robot to write, generating (initially bad) letters and learning from demonstrations is a core aspect of the project. The initial state of the robot and his ability to learn in an obvious way from demonstrations of the child is the key to lend credibility to the activity and to induce the "protégé" effect.

The technical 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 elements $(x_1, ..., x_{70},\ y_1, ..., y_{70})$. We arbitrary chose a set of allograph that define the initial state of generated letters. After the child provided a demonstration of a letter, the algorithm generates a new letter corresponding to the middle point between the last state and the demonstration.

In the following sections, we present various techniques to create the initial state, and different metrics used to compute progression of the robot, tested as hypothesis within our three experiments.

3.2.1 *Generation of initial allographs*

The first question relates to the construction of the initial set of allographs. In previous experiments presented in [11], we built a subspace based on principal component analysis (PCA) of a standard dataset of 214 adult letters (the UJI Pen Characters 2 dataset [18]). We used the first n eigenvectors (in these experiments, $3 < n < 6$) of the covariance matrix generated from PCA to create a subspace. To create new letter shapes, we chose random coordinates close to the origin of this subspace. Each eigenvector provided the direction of a principal deformation of the allograph in human handwriting [10]. But generated "imperfections" of letters were not representative of children deformations: they were reflecting typical defects when adults are writing to fast. Over the following studies, we explored three different ways to generate samples closer to beginners. In our first case study (section 4), we used homework of the child previously provided by his mother, to exaggerate by hand his main defects. This way, the child was going to correct his own kind of mistakes. In the second study (section 5), the child was suffering from visuo-constructive deficits. Since it was difficult for him 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. In the third study 6 we chose to use the middle point between a vertical stroke and correct letters as a starting point for the robot.

3.2.2 *Metrics used for the learning curve of the robot*

The second question focuses on the learning algorithm. In [10], we were projecting children's demonstrations in PCA's subspace in order to compute the middle between that point and the previous state of the robot. Then, we generated the allograph in middle way as the new state of the robot. For the experiments introduced in this paper, we explored two other ideas: In the first study (section 4) we generated a PCA subspace from a small set of allographs we drew arbitrary. Each time the child was providing a demonstration, we added that demonstration to the small set and re-built the PCA subspace. That way, the principal eigenvectors obtained progressively tended to encode the main deformations of letter done by the child. The following algorithm explains the successive steps of this approach:

generate initial dataset D;
generate initial subspace S by PCA of D;
generate initial robot state r (random point in S);
if *robot receives a demonstration* d **then**
  add d to dataset: $D' \leftarrow D \cup d$;
  recompute subspace S' by PCA of D';
  compute coordinates r' of r in S';
  compute coordinates d' of d in S';
  learn the demonstration: $r'' = \frac{1}{2}(r' + d')$;
end

Algorithm 1: learning from demonstration in adaptive PCA subspace

From our perspective, this dynamic subspace was more adapted to the progression of the child, and the sequence of tries performed by the robot looked smoother. However using metrics in subspace can make the learning algorithm too slow in some cases, because consecutive projected demonstrations can sometimes be too far from each other in subspace while they appears similar in Cartesian space. In other studies, we decided to put aside the PCA approach and to always use the middle point in Cartesian space, in order to have a better control over the convergence of the robot tries to the demonstrations.

3.3 Robotic Implementation

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 different devices.

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 [7], 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.

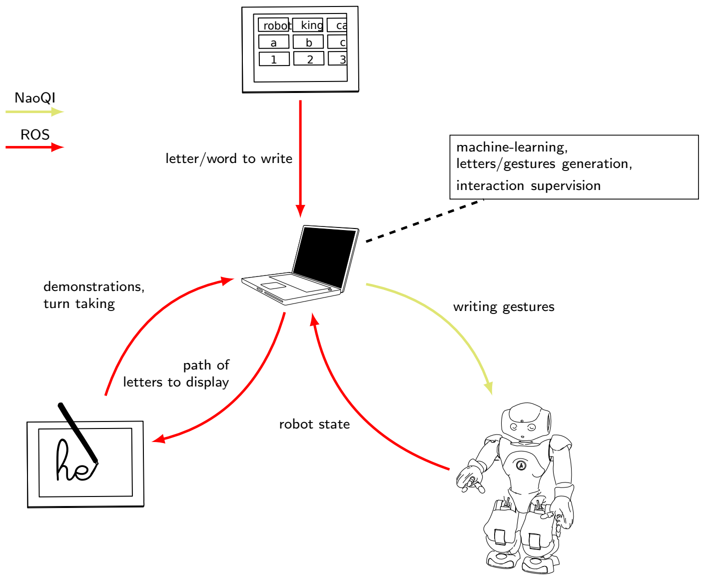


Figure 2: Overview of the system. In total, the system runs about 10 ROS nodes, distributed over the robot itself, a central laptop and Android tablets.

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

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

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 using it in our experiments.

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

4. CASE STUDY 1: VINCENT

4.1 Context

Vincent* is a five year-old child. At school, he has difficulties to learn writing, particularly with cursive letters. From our perspective, Vincent is shy and quiet. He suffers from poor self-confidence much more than any actual writing problem. The experiment was conducted without any therapist, in our laboratory. A parent was here to accompany the child, but he did not intervene during interactions. Children's personalities, conditions and state evaluation were reported by the parent.

4.2 Hypothesis

The CoWriter activity needs a child engaged as interaction leader. With this study we consider the problem of long-term interactions. We hypothesize that with an appealing scenario children can maintain motivation in doing a handwriting activity for an hour over 4 sessions.

4.3 Experimental design and methodology

Our goal was to provide Vincent with an environment that would enable him to sustain engagement over four one-hour sessions, one session per week. We decided to introduce a scenario to elicit a strong "protégé effect" and such induce a stronger commitment. While the child came with low intrinsic motivation in writing exercise, our idea was to use the robot to introduce a new extrinsic motivation: improving letters in order to help the robot.

In our scenario 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 Vincent's help.

Mimi's mission was to explore a mysterious hidden base. Each week, a postal mail contenting a picture of a curious object it found and a few handwritten words about its discoveries. The picture showed itself exploring a dark room of the hidden base (that was actually our laboratory's workshop).

During the three first sessions, Clem (the robot interacting with the child) was waiting for Vincent with the received mail. It let Vincent take a look at the picture and the object,

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

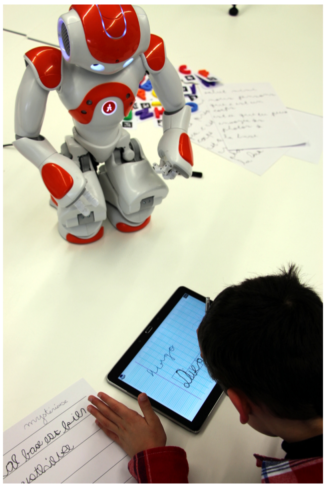


Figure 3: Vincent correcting NAO's attempt by rewriting the whole word. Empty boxes are drawn on the screen to serve as template for the child and to make word segmentation more robust.

and then it asked him to read the message. Finally, Vincent formulated a response and helped the robot to write it.

The fourth and last session was set as a test: Mimi, the "explorer" robot, came back from its mission and challenged Clem in front of Vincent: *"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 confirm the protégé effect: by judging the other robot's handwriting, Mimi would implicitly judge Vincent's skills as teacher, and in turn, Vincent's handwriting.

To complement the intrinsic motivation of helping a robot to communicate with another one, we gradually increased the complexity of Vincent's task to keep it challenging and interesting (first week: demonstration of single letters; second week: short words; third week: a full message – Figure 4).

Vincent had to tell the robot what to write with small plastic letters (visible behind the robot on Figure 3). A third person was here to send the formed word to the robot via the computer.

During the experiment, all robot and child writings on the tablet were recorded on log files. Likewise, we recorded the time date when the child start and finish a demonstration.

4.4 Measures

We measured the commitment of the child with the number of demonstration he provided. We also measured the duration of sessions. During the two last sessions, we recorded the time taken by the child to write demonstrations.

After the experiment we interviewed separately the child and his parent. We asked the child if he though the robot was needing his help, what was le level of the robot before and after the sessions, etc... The goal was to make sure he understood his role in the interaction. The mother was asked if she observed any impact of our activity on the child.

4.5 Analysis

We compared the number of demonstrations provided by Vincent along the 4 sessions (reported on Table 1) and we

Session	S1	S2	S3	S4
Number of demo	23	34	52	46

Table 1: Number of demonstrations provided by Vincent along the 4 sessions.

summed the time spend by the child to write demonstration during the 2 last sessions.

4.6 Results

Overall, Vincent provided 155 demonstrations to the robot. We can see in Table 1 that the number of demonstrations provided by Diego was globally increasing along sessions while the difficulty of the activity was also increasing. Interestingly, as the number of demonstration decreased from session 3 to session 4, the total time spend to write demonstrations is similar: 41.6s in session 3 (∼0.8s per letter) and 41.1s in session 4 (∼0.89s per letter). A explanation of this result could be that since the difficulty was increasing the child spent more time to write his demonstrations. Our activity succeeded in the sense that the child found enough motivation to provide an increasing number of demonstrations, and was still (or even more) carefully in the last session.

It is difficult to make conclusion from the interview of the child, because he could easily be influenced to provide us with positive answers. It still seems that he was aware of his role and the impact of his demonstrations on the state of the robot. To the question "how is the robot's handwriting ?" he answered that the robot "made progresses but still has to take lessons", what shows that he clearly understood that the robot was taking the role of the student and that it improved its writing skills along the sessions.

After the first week, he showed confidence when playing with his "protégé" 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 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 committed into the activity with the robot for a relatively long periods of time (about 5 hours).

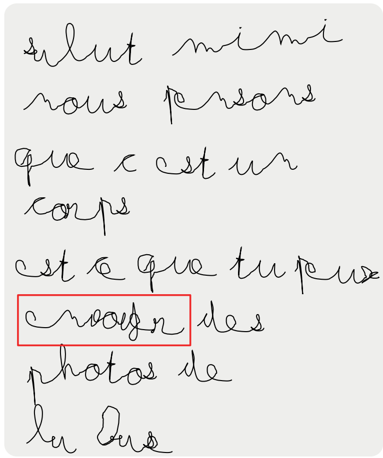
From the parent's perspective, Vincent was actually showing a new motivation in improving his handwriting. He took pleasure to work with the robot and to accomplish his teacher's mission. She confirmed that an affection of the child for the robot took root within the experiment. Finally she saw an improvement of his handwriting and explained that the child "passed from a mix of script and cursive writing up to a full-cursive writing".

But 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 4, 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, which is likely to have a positive impact on his self-esteem.

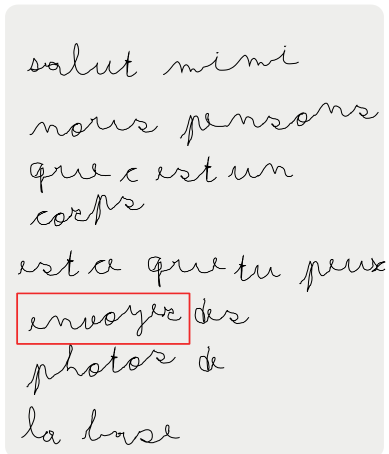
5. CASE STUDY 2 : THOMAS

5.1 Context

Thomas, 5.5 years old child, is under the care of an occupational therapist. He has been diagnosed with visuo-



(a) Initial letter, generated by the robot



(b) Final letter, after training with Vincent

Figure 4: (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".

constructive deficits. He was frequently performing random attempts and then was comparing with the provided template. Thomas 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.

Thomas was working on number allographs with his therapist. During a prior meeting, the therapist provided us with a sequence of numbers written by Thomas. one of the observed problems was drawing horizontally-inverted allographs, mainly for "5".

5.2 Hypothesis

This study focuses on technical adaptations of the CoWriter activity for a child diagnosed with writing deficits. Our objective is to investigate small modifications of the activity adapted to Thomas problems (visuo-constructive deficits and inattention) in order to keep him focused on the activity during forty-minutes sessions, and to evidence to the child that the robot is progressing by dint of his demonstrations.

5.3 Experimental design and methodology

The experiment was conducted in the therapist's office (four sessions spanning over 5 weeks). We assumed that a scenario like the one we used for Vincent would not be usable with Thomas. 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 work with numbers.

Since Thomas was frequently drawing horizontally-inverted numbers, or even unrecognisable 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 Thomas 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 Thomas about the right final allograph's shape, we made the robot able to recognize such a drawing, and, when it occurred, to use the phrase: *"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 direction?"*

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 possibility to enter letters or words, and to switch to another activity (robot telling a story if the child needs a short break).

5.4 Measures

5.5 Analysis

5.6 Results

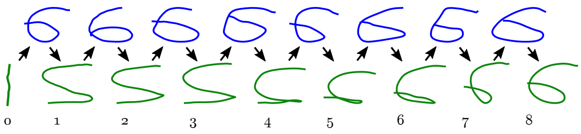


Figure 5: Demonstrations provided by Thomas for the number "6" (top row) and corresponding shapes generated by the robot. After eight demonstrations, Thomas decided that the robot's "6" was good enough, and went to another character: in that respect, he was the one leading the learning process of the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

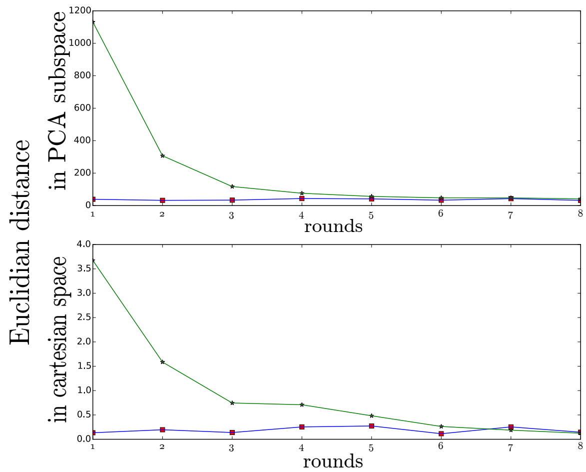
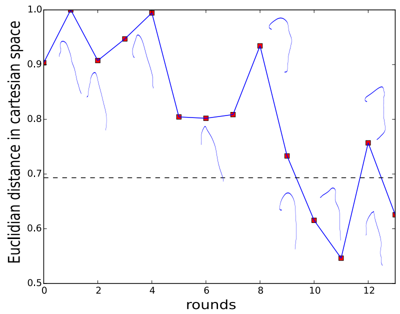


Figure 6: Two metrics to assess the handwriting progresses: Euclidean distance in the subspace of the number dataset (top figure) or in Cartesian space (bottom figure). Green lines represent the robot performance, blue lines performance of the child. The round IDs correspond to the demonstrations pictured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

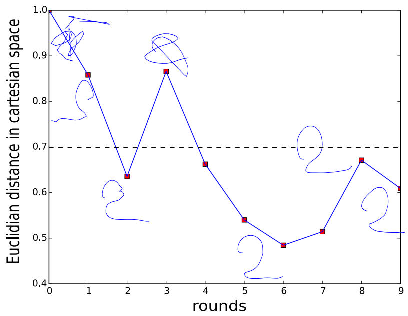
Despite his attention deficit, Thomas was able to remain engaged in the activity during more than forty minutes in each session. In total, 55 allographs out of 82 demonstrated by the child were acceptable considering our threshold (with a progressive improvement from 13 out of 28 in the first session 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). 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 samples.

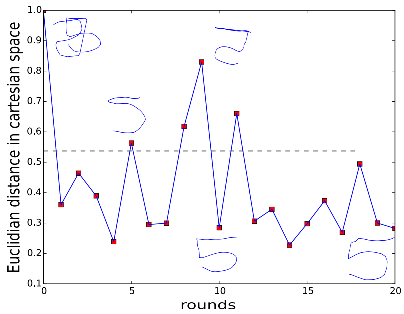
Since the robot's handwriting started from a simple primitive (a stroke), each time Thomas succeeded to have his demonstration accepted by it, the robot's improvement was clearly visible (as measured in Figure 6). This led to a self-rewarding situation that effectively supported Thomas' engagement.



(a) number 1



(b) number 2



(c) number 5

Figure 7: Improvement of Thomas demonstrations for some numbers: a) drawing the allograph of the number 1, b) the number 2 and c) the number 5. Thomas 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.

6. CASE STUDY 3: WHEN CHILDREN EVALUATE THE ROBOT

6.1 Context

Each of previous studies was adapted to individual subjects : we used a special design for each case in order to sustain the child's engagement. In our next experiment, we conducted case studies with eight children using a single 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 know the allographs of cursive letters.

6.2 Hypothesis

The main purpose of this study is to test the ergonomic aspects of CoWriter. When introducing the robot, we did not provide scenario and gave to children minimal explanations. We then observed how easily children assumed the role of the teacher and how seriously they tried to help the robot.

6.3 Experimental design and methodology

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 present to explain the rules of the game and tablet usage. As in the previous experiment, children were provided with 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. We also provided the allograph's template if the child asked for.

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 new generated sample by the robot were calculated as 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 responsibility of the teacher.

We added two buttons on the tablet interface: a green one with a "thumbs up", and a red one with a "thumbs 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 measure 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 became possible to estimate if a child is playing seriously given correlation between his evaluation and robot's actual progression.

6.4 Measures

6.5 Analysis

6.6 Results

All children maintained their engagement during the whole sessions. They provided on average 42 demonstrations per session. All children used evaluation buttons and had preference to reward the robot (in total, 99 rewards and 33 punishments were recorded).

Since sessions took place over only two weeks, we did not studied possible handwriting remediation in children, but 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). The score is calculated as the average of euclidean 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 template[3]. 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 measure 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 evaluation at time i ($R_i^n = 0$ if no evaluation occurred at time i , $R_i^n = 1$ if a reward occurred at time i and $R_i^n = -1$ if a punishment occurred at time i), and $\overline{R}_i$ be the actual evaluation at time i. For each n^{th} generated sequence of 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 $(S^n)_n$, which is assumed to be Gaussian:

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

where ϕ denotes the cumulative distribution function of the standard normal distribution, μ the mean and σ the deviation of the generated scores $(S^n)_n$. As a result, we found that 5 of the 8 children obtained a score of evaluation significantly hight ($p(\overline{S}) < 0.05$). Score of evaluation p-values of each child is reported in the second-to-last column of Table 2.

We also studied correlation between children's evaluations and their own progression. The analysis was conducted in the same way, using distances between children demonstrations and reference allographs to compute children progressions. 3 of 5 children that played "seriously" obtained score of evaluation of their own progression significantly high (last column of Table 2). For those 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.

[3] `http://www.education.com/slideshow/cursive-handwriting-z/`

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 2: 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 ?

7. CONCLUSION

This paper provides 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). These designs of long-term interactions provide opportunities for studying and improving actual impact of human-robot activities as education tools.

According to observations, we assume that children understood the robot was progressing thanks to their demonstrations. It had an effect on their motivation: some of them was training at home between to sessions in order to give a better teaching to the robot at the next time. 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 how much he was satisfied with 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: • it is possible to detect if the child is playing seriously or not (a non-serious child may provide unrecognisable 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). • We can reinforce the learnt allograph when the robot receives a good evaluation, or make it forget the allograph when it receives a bad evaluation.

After all those experiments, we now have a large database of children writings that could be used to generate more interesting subspaces by PCA and robot initial states. Recurrent neural networks (RNN) for handwriting recognition and generation [8] could also be used to generate children-like handwriting.

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