

Learning by Teaching a Robot

The Case of Handwriting

© PHOTOCREDIT

By Séverin Lemaignan, Alexis Jacq, Deanna Hood, Fernando Garcia, Ana Paiva, and Pierre Dillenbourg

A Different Paradigm for Educative Robots

Thomas (all children's names have been changed) is five and a half years old and has been diagnosed with visuoconstructive deficits. He is under the care of an occupational therapist and tries to work around his inability to draw letters in a consistent manner. Vincent is six and struggles at school with his poor handwriting and even poorer self-confidence. Whereas Thomas is lively and always quick at shifting his attention from one activity to another, Vincent is shy and poised. Two very different children, each one facing the same difficulty to write in a legible manner. Additionally, hidden beyond these impaired skills, psychosocial difficulties arise: they underperform at school. Thomas has to go for follow-up visits every week, and they both live under the label of "special care." This is a source of anxiety for the children and for their parents alike.

Remediations for handwriting difficulties traditionally involve long interventions (at least ten weeks [6]), essentially consisting of handwriting training with occupational therapists and primarily addressing the motor deficits. Improvements in self-confidence and anxiety occur (at best) as a side effect of the children improving their handwriting skills and, consequently, improving their performances at school. In this article, we present a new take on this educative challenge: a remediation procedure that involves a bad writer robot that is taught by the child. By building on the learning by teaching paradigm, not only does the child practice handwriting, but also, as they take on the role of the teacher, they positively reinforce their self-esteem and motivation: their social role shifts from the underperformer to the one who knows and teaches. In addition, by relying on a robot, we can tailor the exercises and the learning curve individually to each child's needs as we will show in this article.

Digital Object Identifier 10.1109/MRA.2016.2546700
Date of publication: 9 May 2016

Learning by Teaching Handwriting

The learning by teaching paradigm, which engages the student in the act of teaching another, has been shown to produce motivational, metacognitive, and educational benefits in a range of disciplines [14]. 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 prove difficult if the child is the lowest performer in the class. In some cases, it may be appropriate for a peer or a teacher to simulate a naive 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 that 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 [4] and less often to physical skills (such as calligraphy [12]). Looking at the converse (humans teaching robots), Werfel notes in [18] that most of the work focuses on the robot's benefits (in terms of language [15] or physical [13] skills, for example) rather than the learning experienced by the human tutor themselves. Our work concentrates on this latter aspect: by demonstrating handwriting to a robot, we aim at improving the child's performance. A robotic learning agent that employs the learning by teaching paradigm has previously been developed by Tanaka and Matsuzoe [17]. In their system, children learn vocabulary by teaching the NAO robot to act out verbs. The robot is teleoperated (Wizard of Oz) and mimics the actions that the children teach it but with no long-term memory or learning algorithm in place. Our project significantly extends this line of work in two ways. First, by investigating the context of the children's acquisition of a challenging physical skill (handwriting) and second by proposing a robotic partner that is fully autonomous in its learning.

Agency and Commitment

We also investigate a particular role for a robot in the education of handwriting: not only is the robot actively performing the activity by drawing letters, but it also does so in a way that engages the child in a very specific social role. The child is the teacher in this relationship, and the robot is the learner: the child is to engage in a (meta) cognitive relationship with the robot to try to understand why the robot fails and how to best help it. Here, the robot is more than just an activity facilitator or orchestrator—its physical presence and embodiment induce agency and anthropomorphizing and cognitively engage the child into the learning activity (be it consciously or not).

The commitment of the child into the interaction builds on a psychological effect known as the *protégé effect* [2]: the teacher feels responsible for his student, commits to the student's success, and possibly experiences the 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 [2]. We rely on this cognitive mechanism to reinforce the child's commitment into the robot-mediated handwriting activity, and we show sustained child-robot engagement over extended periods of time (several hours spread over a month).

For these two reasons, our approach is to be distinguished from previous works on educational robotics. Most of these do not consider the agency induced by the robot beyond its motivational aspect (playing with an interactive partially autonomous device induces excitement—at least, for the short term). In our case, the role of agency is stronger: it induces metacognition (“I am interacting with an agent, so I need to reflect on how to best teach him”), which is beneficial for the learning process; it also induces a protégé effect (“I want my robot-agent to succeed!”), which also supports the commitment of the child into the interaction for longer periods of time. These initial considerations can be turned into a set of research questions:

- How to develop a fully autonomous robotic system that produces believable handwriting, fosters interaction, and adequately learns from the children's demonstration?
- Can such a system be accepted by children and practitioners alike and eventually be integrated in existing educative and therapeutic practices?
- Can we build and evidence interactions that sustain children's engagement over extended periods of time?
- Is this novel approach effective?
- Do we evidence actual handwriting improvements by children facing difficulties?

Implementation of the Interaction

Figures 1 and 2 illustrate our general experimental setup: a face-to-face child-robot interaction with an autonomous Aldebran's NAO robot. A tactile tablet is used for both the robot and the child to write. During a typical round, the child requests that the robot write something (a single letter, a number, or a full word) and pushes the

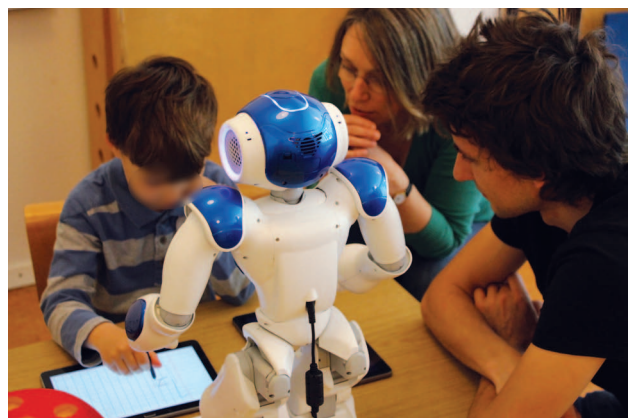


Figure 1. Thomas teaching a NAO robot how to write numbers with the help of an occupational therapist. (Photo courtesy of Séverin Lemaignan.)

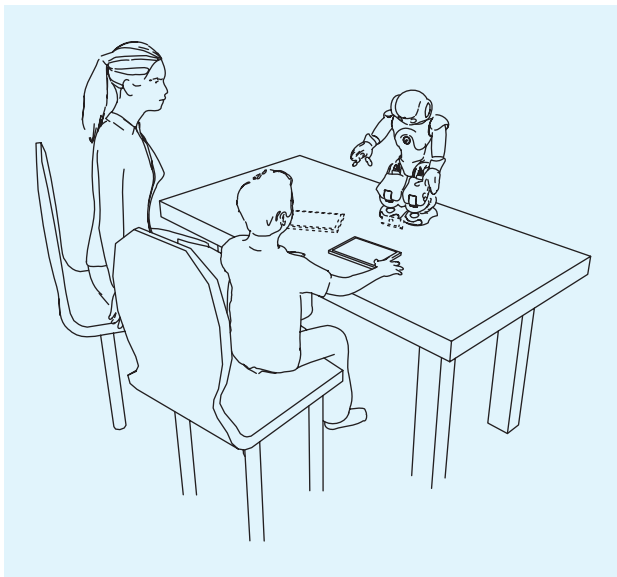


Figure 2. Our experimental setup: the robot writes on a tactile tablet, and the child then corrects the robot by overwriting its letters with a stylus. An adult (either a therapist or an experimenter) guides the work (prompting, turn taking, etc.). For some studies, a second tablet and an additional camera (dashed) are employed.

tablet toward the robot. The robot writes on the tablet by gesturing the writing in the air, the letters actually being drawn by the tablet application itself. The child then pulls back the tablet, corrects the robot's attempt by writing herself on top of or next to the robot's writing (see Figure 3), and sends her demonstration to the robot by pressing a small button on the tablet. The robot learns from this demonstration and tries again.

Since the children are assumed to take on the role of the teachers, we had to ensure they would be able to manage the turn taking and the overall progression of the activity (moving forward to the next letter or word) by themselves. In our design, the turn taking relies on the robot prompting for feedback once it is done with its writing (through simple sentences, such as "What do you think?") and pressing on a small robot icon on the tablet once the child has finished correcting. In our experiments, once introduced by the experimenter, both steps were easy to grasp for the children. Implementing such a system raises several challenges: first, the acquisition, analysis, and learning from hand-written demonstration, which lies at the core of our approach, necessitates the development of several algorithms for the robot to initially generate 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 state machine implementing the high-level behavior), spread over several devices (the robot itself, one laptop, and up to four tactile tablets for some of the studies that we conducted). We relied on the Robot Operating System (ROS) to ensure the synchronization and communication between these modules.

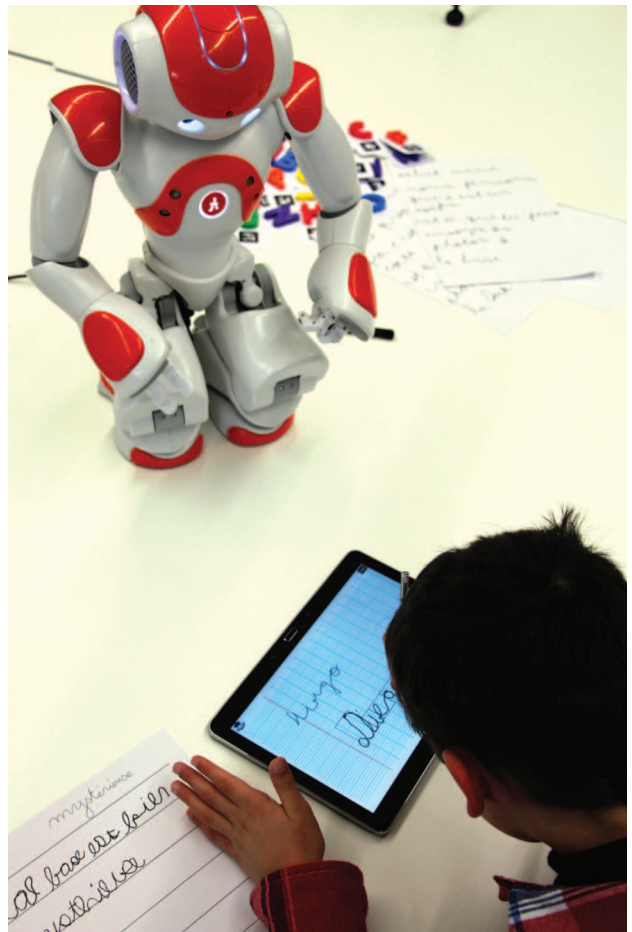


Figure 3. Vincent correcting NAO's attempt by rewriting the whole word. Empty boxes are drawn on the screen to serve as a template for the child and to make letter segmentation more robust. (Photo courtesy of Séverin Lemaignan.)

Generating and Learning Letters

Since our application is about teaching a robot to write, generating (initially bad) letters and learning from writing demonstrations are core aspects of the project. The main insight for both the generation and the learning of letters is to reason about the shape of the letters in their eigenspace, instead of the natural Cartesian space. The eigenspace of each letter is spanned by the first n eigenvectors (in our experiments, $3 < n < 6$) of the covariance matrix generated from a standard dataset of adult letters (UJI Pen Characters Data Set, version 2 [11]). Our method, based on a principle component analysis (PCA), is presented in [5]. New letters are generated by varying the weightings in linear combinations of these eigenvectors with distortions that are actually plausible handwriting errors: they are exaggerations of variations of writing styles that naturally occur among adult writers. Figure 4 shows examples of a deformed "g" generated with such a technique. The same shape model can also be used to classify demonstrations, assess their quality, and learn from them. Figure 5 shows, for example, nine allographs of "h" written by a six-year-old child, along with the reference shape. By projecting each of the demonstrations onto the eigenspace

of h [Figure 5(b)], we observe that:

- The different allographs can be clustered (with a k -means or mean-shift algorithm) by their visual styles.
- We can compute a Euclidian distance to the reference letter to assess the topological proximity of the demonstration with the expected letter, thus, providing a quantitative metric of writing performance.

The algorithm for machine learning then becomes a simple matter of converging at a specific pace toward the child's demonstration in the eigenspace. Figure 6 illustrates the process with a complete learning cycle of the number six.

Robotic Implementation

Our system is embodied in an Aldebaran NAO (V4 or V5, depending on the study) humanoid robot. This choice is motivated by its approachable design [3], size (58 cm), inherently safe structure (lightweight plastic) making it suitable for close interaction with children, low price (making it closer to what schools may afford in the coming years), and ease of deployment in the field. Robotic handwriting requires precise closed-loop control of the arm and hand motions. 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 synchronized tablet.

The overall architecture of the system is, therefore, spread over several devices: the NAO robot itself, which we address via both an ROS application program interface (API) and the Aldebaran-provided NAOqi API, one to four Android tablets (the main tablet is used to draw 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

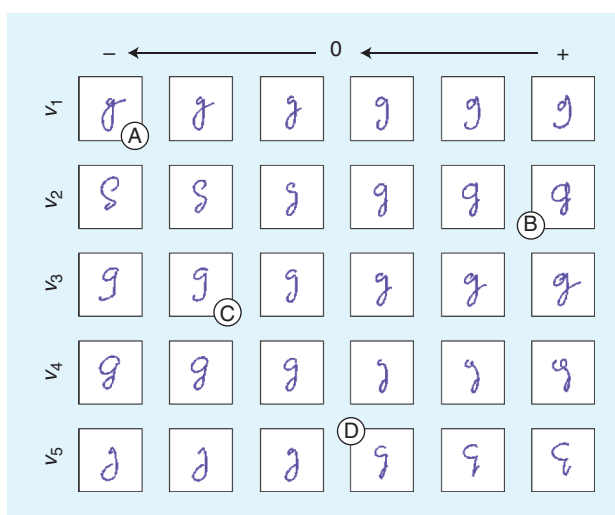


Figure 4. Generating bad letters: effect of independently varying the weightings (columns) of the first five eigenvectors (rows) of the shape model of the letter “g.” Examples (a)–(d) illustrate how the PCA-based approach allows for the *automatic* generation of letters whose errors are typical of children handwriting: (a) has too large a bottom loop, (b) has a wide top loop, the bottom loop of (c) is not correctly closed, the top loop of (d) is not closed, etc.

interaction in a synchronized fashion), a central laptop running the machine-learning algorithms, the robot's handwriting gesture generation (based on the NAOqi inverse kinematics library), and the high-level control of the activity (relying on PYROBOTS [10] and a custom finite state machine). Since the system does not actually require any central-processing-unit-intensive processes, the laptop can be removed, and the whole logic can be run on the robot. Due to the relative difficulty to deploy and debug ROS nodes directly on the robot, the laptop remained, however, convenient

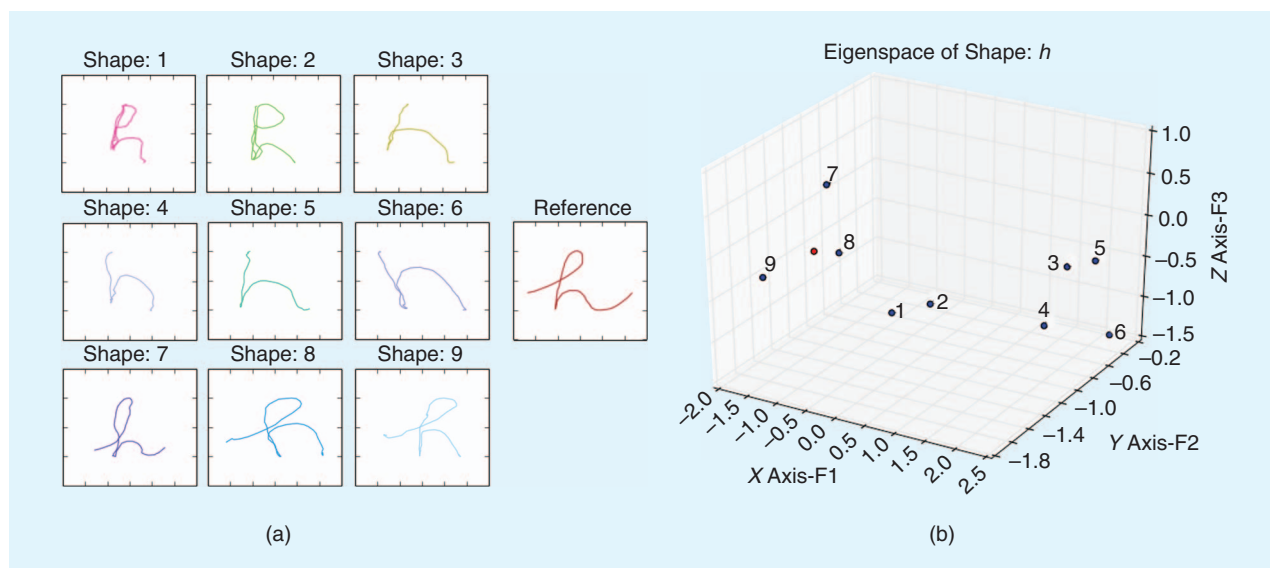


Figure 5. Projecting demonstrated letters onto the eigenspace generated from the reference dataset effectively clusters the samples according to their topological similarity. Allographs that are similar to the reference are close to it in the eigenspace. (a) Nine allographs of the cursive “h” next to the reference, and (b) the same samples normalized and projected in the eigenspace spanned by the first three eigenvectors: clusters arise that actually match writing styles.

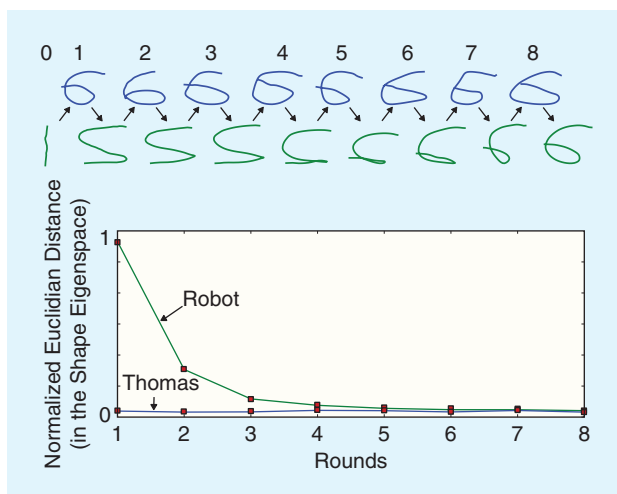


Figure 6. The demonstrations provided by Thomas for the number 6 (top row) and corresponding shapes generated by the robot. The plot beneath shows the distance to the reference shape (in the eigenspace of the shape) to Thomas' demonstrations and to the robot's attempts. After eight demonstrations, Thomas decided that the robot's 6 was good enough and switched to another character. In that respect, he was the one leading the learning process of the robot.

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 (the primary repository is https://github.com/chili-epfl/cowriter_letter_learning). The details of the technical implementation are available in [5].

Field Studies

The system has been deployed and tested in several situations: in three different schools (more than 70 children aged five to eight and relatively short duration interactions), in an occupational therapy clinic (eight children, each interacting for several hours with the system), and during two case studies that each lasted several weeks. We report, hereafter, the



Figure 7. The first field studies were focused on technical validation with more than 70 pupils interacting with the robot over short periods (between 10 and 25 min), either alone or in small groups. (Photo courtesy of Séverin Lemaignan.)

main design choices and results for each of these studies and experiments. The interested reader can find supplementary details in [7], [5].

System Validation at Schools

Over the two years of the project, we conducted four studies in schools (Figure 7). These experiments were meant to technically validate the system (is it actually able to autonomously write and learn from handwriting demonstrations?) and test the interaction (is the apparatus easy to grasp and to interact with for children?). We also studied the initial acceptance of the robot in the school environment (through several formal and informal discussions with teachers) and how children engage with the robot (and maintain or not this engagement). Critically, these studies were conducted with whole classes: we decided not to select specifically underperforming children as having more children (73 in total) was beneficial for these preliminary studies. In addition, due to ethical concerns, this would have required complex organization with the school, which we wanted to avoid at the validation stage.

System Validation

From a technical perspective, the system achieves an acceptable level of reliability and allows a technically sound autonomous interaction. For instance, during the second school study (School B), the robot withstood interactions that lasted for a total of 160 min. During this time, the robot wrote 335 letters, 152 of which were in response to demonstrations received from the 21 children. Technical intervention was only required for the three instances where the robot fell during that day. Otherwise, the technical components of the system operated autonomously and as expected with all the groups of children. Due to the modular software architecture (mostly independent ROS nodes), the occasional crashes occurring during others studies were usually quickly resolved by relaunching the faulty node alone and did not significantly impact the interaction. The otherwise technical limitations were related to some letters or writing styles (most notably, the ones requiring multiple strokes per letter) not being adequately processed by the learning algorithm. Support for such letters was added as a follow-up to the validation studies.

Acceptance

Children's recognition that the robot is writing by itself is critical for our approach to be effective. When asked, no child indicated that they did not believe that the robot was writing by itself. There were, at times, questions about the robot's writing without a pen at the beginning of the interaction, but when advised that the robot tells the tablet what it wants to write, this was accepted by the children. During two focus groups organized with teachers, they welcomed the approach and recognized it as useful and promising; this was a posteriori confirmed by multiple spontaneous contacts made by parents and therapists who were looking forward to using the system with their children.

Table 1. The Levels of With-Me-Ness.

Child	1	2	3	4	5	6	<i>M</i>	<i>SD</i>
<i>W</i>	79.4%	81.6%	90.5%	87.9%	90.7%	80.9%	85.2%	5.1

Percentage of interaction time during which the child was effectively focusing her attention on the task. The six children are those from the second study at School A. Interaction duration: $M = 19.6$ min, $SD = 1.58$. Results taken from [9].

Sustained Engagement

Factually, the children engaged into the teaching activity: in the study at school B, for instance, they demonstrated an average of 10.9 demonstration letters [standard deviation (SD) = 4.4] for an average session duration of 11 min. In nine out of the 14 sessions (64%), the robot received demonstration letters even after reaching the final stage of the interaction, suggesting an intrinsic motivation to further engage in the interaction. We also conducted a quantitative assessment of the engagement levels of the children. Table 1 reports the levels of with-me-ness of the children during the second study at school A. *With-me-ness* is a quantifiable precursor of engagement: it measures the percentage of time spent by the child focusing on the task at hand [9]. We compute it by first estimating the focus of attention of the child over the course of the interaction (using real-time six-dimensional head pose estimation) then, by matching this measured focus of attention with the expected attentional targets. For instance, when the child is supposed to write a demonstration, we expect her to look at the tablet if she is actually engaged into the task; when the robot is telling a story, we expect the engaged child to look at the robot, etc. The average with-me-ness is well above 80% and confirms that the children were very much engaged in these 20 min of interaction with the robot, paying close attention to the task.

Clinic Study: How Children Take on the Role of a Teacher

Context, Study Design

This experiment was conducted to study how easily children with actual deficits take on the role of a teacher and to what extent they adopt this role (measuring actual handwriting improvements was not a primary goal of this experiment). The experiment took place at an occupational therapy clinic in Normandy, France. Eight children participated, selected by the occupational therapist based on their ages and type of deficit (all related to handwriting). Given their ages (six to eight years old) and school year, all of these children would be expected to know how to correctly shape cursive letters. Each child attended, three times, a 1-h-long session spread over two weeks (except for two of them who only attended one session). The experimenter's role was limited to the explanation of the task and the basic tablet usage. The children were provided with two tablets: one to choose the words (or letters) to teach to the robot, and one to write.

We only provided the children with minimal explanations on the task (they would have to help the robot to improve its

writing style) so as to assess if and how the children would naturally take on the role of the teacher. We additionally assessed how seriously they engaged into helping the robot through two additional buttons on the tablet: a green thumbs up and a red thumbs down. The children were told to freely use them to evaluate the robot's improvements (thumbs up to give positive feedback, thumbs down to give negative feedback). Our assessment builds on the hypothesis that the more the child provides feedback to the robot, the more they assume the role of a teacher. Then, by correlating the feedback with the actual performance of the robot, we can measure to what extent the children are adopting their teacher role: if their feedback does correlate with the actual performance of the robot, the child has likely successfully adopted the teacher role.

Results

All children maintained their engagement during the whole sessions. They provided, on average, 42 demonstrations per session. All children used the feedback buttons (in total, 99 thumbs up and 33 thumbs down were recorded). This indicates that they were all able to engage into playing the role of a teacher. To study the correlation between the children's feedback and the actual improvements of the robot, we estimate the robot's progress as the difference between an initial score (Euclidian distance between the shape drawn by the robot at its first attempt and the shape of the reference letter) and the robot's score at the current round of demonstrations. We then correlate this progress to the positive or negative feedback provided by the children (details of the method as well as the complete results are presented in [7]).

We found that the feedback of five out of the eight children did significantly correlate with the actual performance of the robot. This indicated that these children were effectively taking on the teacher's role and were seriously providing feedback to the robot. The observation of the three remaining children revealed a variety of behaviors (for instance, one was actually rating how nice the robot was, and another one had rather artistic writing style preferences that were independent of the actual legibility of the robot), but none of these children adopted a playful-only behavior toward the robot. To summarize, this experiment shows that children with actual handwriting impairments accept the robot well, can commit themselves into long interactions, and adopt the role of the teacher (as evidenced by both the number of writing demonstrations they provided and their self-inclination to give adequate feedback to the robot).

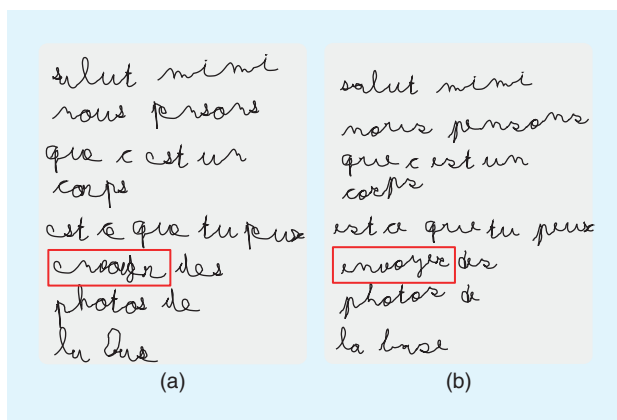


Figure 8. The text (in French) generated by the robot before and after a 1-h-long interaction session with the child. The red box highlights one instance of striking improvement of the robot's handwriting legibility "envoyer." (a) Some initial text, generated by the robot, and (b) the final text, after training with Vincent.

Case Study 1: Vincent

For the first case study, we invited and followed Vincent, a six-year-old child, once per week over a period of a month. Our primary aim was to address the question of whether we could sustain Vincent's engagement and commitment to the writing activity over such a period. The study took place at our laboratory (Figure 3), and we chose to design the activity around a storyline meant to be attractive for a six-year-old boy: one of our NAOs was away for a mysterious scientific mission, and it needed the support of another one—which would remain at the laboratory—to interpret curious pictures that were sent every week. Vincent had to help the second robot understand the pictures, and since the two robots had somehow, beforehand, agreed to communicate with letters written like humans (i.e., handwritten), Vincent also had to help the robot to write good-looking letters (because, well, this robot was terrible at writing!). The experimental setup was similar to Figure 2, except that Vincent had to tell the robot what to write with small plastic letters (visible behind the robot in Figure 3).

To supplement 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 [the first week: demonstration of single letters; the second week: short words; the third week: a full letter (Figure 8)]. The last session was set as a test: the "explorer" robot had come back from its mission, and it actually challenged the other robot 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 evidence the protégé effect: by judging the other robot's handwriting, the explorer robot would implicitly judge Vincent's skills as a teacher and, in turn, Vincent's handwriting.

Results

Over the whole duration of the study, Vincent provided 154 demonstrations to the robot, and he remained actively

engaged over the four weeks. The story was well accepted by the child, and he seriously engaged with the game. After the first week, he showed good confidence in playing with the robot, and by the end of the study, he had built affective bonds with the robot as evidenced by several letters he did send to the robot after the end of the study (one of them four months later) to get news. This represents an initial validation of our hypothesis: our system can effectively keep a child engaged with the robot for a relatively long period of time (about 5 h spread over a month), and we can build a tutor/protégé relationship.

No hard conclusion can be drawn in terms of actual handwriting remediation as we did not design this study to formally assess possible improvements. However, as visible in Figure 8, Vincent was able to significantly improve the robot's skill, and he acknowledged that he was the one helping the robot during post hoc interviews. In that respect, Vincent realized that he was good enough at writing to help someone else. The fact that Vincent adopted the role of a teacher is further supported by feedback sent by Vincent's parents a week after the end of the experiment: "Vincent's handwriting has changed over the last weeks, going from a mix of stand-alone and cursive letters to full words in cursive. This requires a lot of effort and concentration from him, but he did succeed during the sessions with the robot as he knew he had to show a consistent style of writing to the robot."

Case Study 2: Thomas

The second long-term study was designed in collaboration with an occupational therapist in Geneva and aimed at deploying the system on the longer term with a real therapeutic case. Thomas is a 5.5-year-old child. He has been diagnosed with visuoconstructive deficits, which translate into difficulties for him to consistently draw letters. In addition, focusing on a task is difficult for Thomas, who tends to rapidly shift his attention to other things. Since the robot's learning algorithm requires repeated demonstrations of similarly shaped letters to converge, the occupational therapist was especially interested in observing if the robot would induce a strong enough motivation for Thomas to focus on producing many regular consistent letters, thus, overcoming his deficit.

The experiment took place at the therapist's clinic (four sessions spread over five weeks). Contrary to Vincent's experiment, we chose not to introduce any backstory beyond a simple prompt ("the robot wants to participate in a robotic handwriting contest, will you help him prepare?") only provided during the first session. Hence, we also tested, during this case study, if the robot (and the protégé effect) would induce by itself a strong enough intrinsic motivation to keep the child engaged over the five weeks. The occupational therapist had recently carried out activities with Thomas on writing numbers, so we decided with her to focus on these as well: Thomas would use a secondary tablet to tell the robot what number to write and would then correct the robot's attempts, such as in the other experiments. Figure 6 shows the attempts/corrections cycles

that occurred during one of the sessions on the number six.

Since Thomas would frequently draw mirrored numbers or hard-to-recognize shapes (see Figure 9), the learning algorithm of the robot initially tended to converge toward meaningless scribbles. We addressed this issue by having the robot refuse allographs that were too far from the reference shape (the robot would, instead, say “I’m not sure I understand what you are drawing...”) so that the child had to pay good attention to what he would demonstrate to the robot. Also, to make the robot’s progress evident, we modified the initialization step of the learning algorithm to start with a roughly vertical stroke instead of a deformed number (see the initial state in Figure 6).

Results

Despite his attention deficit, Thomas was able to remain engaged in the activity during more than 40 min in each session (a long time for a five-year-old). 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 the number before actually sending it to the robot five or six times (the tablet lets children clear their drawing and try again before sending it). According to the therapist, it was the first time that Thomas was seen to correct himself in such a way, explicitly having to reflect on how *another agent* (the robot) would interpret and understand his writing. Figure 9 shows how he gradually improved his demonstrations for two different numbers. Since the robot’s handwriting started from a simple primitive (a stroke), each time Thomas succeeded in having his demonstration accepted by the robot, the improvement was clearly visible (as shown in Figure 6). This led to a self-rewarding situation that effectively supported Thomas’ engagement.

Summary of the Findings and Discussion

The four school studies, the experiment at the clinic, and the two case studies provide the first broad picture of how a robot-based remediation to handwriting is accepted by the children and practitioners and what outcomes can be expected. In total, more than 80 children have interacted with the system, for a total duration of more than 38 h, in multiple experimental configurations (individual interaction versus pairs versus groups; at school, in the laboratory, at an occupational therapy clinic; short interactions versus long repeated interactions; five- to eight-year-old children). We summarize, hereafter, the main findings from these experiments and discuss some of the critical points of our approach.

Technical Assessment

We set ourselves the challenge of developing an autonomous robotic system able to perform handwriting tasks with children in real-world environments. The system performed generally well: the children had no issues interacting with

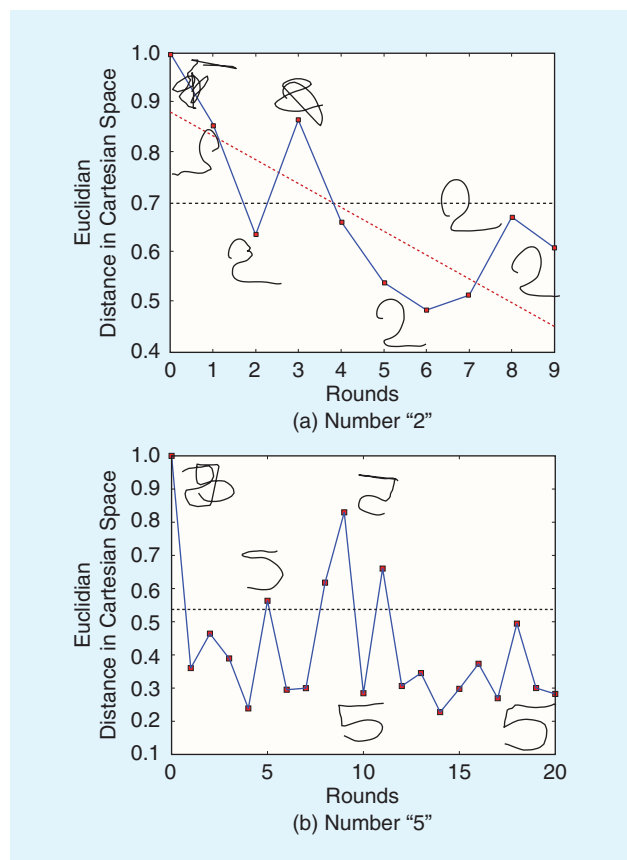


Figure 9. The normalized distance between Thomas’ demonstrations and reference allographs for the numbers (a) 2 and (b) 5. The horizontal dashed line corresponds to the threshold for the robot to accept a demonstration. Thomas’ progress is visible in these figures: we find a significant negative regression equation ($r = -0.023$, $F(1,19) = 8.69$, $p < 0.02$, and adjusted $R^2 = 0.461$) for the number 2 (dotted red line), indicating that Thomas’ shapes are getting closer to the reference. The regression is not significant for the number 5, but we can observe that after about ten repetitions, all the demonstrations are deemed of acceptable quality by the robot.

the robot, the robot experienced relatively few crashes, and those crashes did not significantly impair the interactions. The system has furthermore proved robust enough to conduct several hour-long experiments. However, we also found that the level of expertise required to deploy and operate our system still makes the presence of an experimenter mandatory at all times. Nontrivial technical developments may be required to reach a level of usability suitable for a broader nonexpert audience.

Acceptance

The acceptance of the robot in an educative and/or medical context was not initially obvious, and the attitude of practitioners toward the robot varied. For instance, whereas Thomas’ therapist did voluntarily contact us (after hearing about the project on the radio) and readily involved herself in the design of the experiment, we had less positive feedback from other practitioners: in one instance, we contacted a local group of school psychologists to present the project: after the meeting, the opinions were definitively mixed, with

some therapists willing to conduct actual experiments with their children and others not quite as enthusiastic. Expectedly, the reaction of the children to the robot was good: they enjoyed interacting with the system, and, as we have shown, they actually committed to their teacher role over extended periods of time. The teaching situation was well accepted, and technical constraints, such as having the robot to only gesture writing on the tablet instead of actually physically writing with a pen, were not actually raised as issues.

Engagement

We measured the engagement of the children by three different means: the number of demonstrations they provided to the robot, the amount of qualitative feedback they gave to the robot (in the Clinic experiment), and to what extent they were focusing on the task (measure of the with-me-ness). Independent of the experimental setting, it appears that the children engage easily with the interaction. More interestingly, we show in the Clinic experiment that they generally take on the role of a teacher easily, that they act out this role seriously (and not only playfully), and that they can assume this role over an extended period of time. Designing a system that keeps children engaged over several hours is especially important for handwriting remediation, and we show in the case studies that even children as young as 5.5-years-old, such as Thomas, were able to do so. This seems to indicate that our approach could be relevant for a broad range of ages.

Another finding relates to the protégé effect: as seen with Vincent (when he sends us a mail several months later to know how the robot is doing with its writing) or with Thomas (when he realizes that the robot does not understand and, consequently, quickly improves his own writing to better help the robot), our system does elicit a protégé effect that not only helps the children to remain engaged in their teaching over several weeks, but also positively impacts their learning process (Vincent strives to write in a consistent manner as does Thomas). This supports a posteriori our choice to build an interaction situation based on the learning by teaching paradigm.

Remediation Efficacy

Vincent's case study did provide us with initial material to evidence handwriting improvements (Figure 8), and the study with Thomas provides further data, both quantitative (Figure 9) and qualitative (feedback from the therapist that points how Thomas is much better at drawing consistent shapes in a repeated manner as well as reflecting on his own performance by training several times before actually sending a demonstration to the robot). We must, however, remain cautious here regarding the actual role of the system: although the children were the ones deciding what to teach to the robot, and the robot was autonomously learning and responding, the role of the adults (the experimenters or the occupational therapists) should not be underestimated. Beyond the normal explanations of how to operate the tablet and how to interact with the robot, the

adults played the role of a facilitator in each of the studies by prompting the children to comment on the robot's performance, suggesting possible corrections, or proposing to try another letter/number/word. This facilitation not only compensates for the possible shortcomings of the interaction but also is a fundamental part of the learning process itself. In that respect, our robot is essentially a tool that creates a favorable learning situation for the child and where the adult (be it a teacher or a therapist) keeps their entire educative role.

Conclusion

We believe that this research provides a novel perspective on educative robots at several levels. Namely, we show that:

- Robots in an educative context are certainly relevant and effective beyond science, technology, engineering, and mathematics teaching.
- We can successfully transpose the well-established learning by teaching paradigm from education sciences to robotics, even in a complex form: handwriting is a difficult physical skill, and the robot learns and interacts autonomously, and the child is responsible not only for the teaching, but also for the teaching orchestration by managing the turn taking and the progression of the activity.
- Blending machine-learning techniques with human-robot interaction allows for building a believable agent that induces social commitment.
- This social commitment induces cognitive engagement of the child with the robot, which is a key learning lever as it elicits reflective metacognitive mechanisms on the learning task.
- We have been able to sustain a long-term interaction (several hours) involving a task that would typically be considered repetitive and challenging by the children.

Supported by several field experiments, our initial results are promising as we ultimately evidence handwriting improvements. It is, however, still early to quantify the lasting effects of this remediation: handwriting is a complex cognitive skill that builds on many individual and social factors. Self-confidence is one of them. Our approach endows the child with the role of a teacher who can help a robot: we expect it may as well help some children to recover self-esteem and self-confidence by putting them in a positive gratifying role. The experiments that we have conducted so far do not allow us to confirm this hypothesis yet, and more research will have to be conducted in this direction.

Possible Ethical Concerns

There are two aspects of this research that should be discussed in terms of their possible ethical implications: the perceived role of the robot vis-à-vis the real teachers, and the implications of the mentor-protégé relationship for children, especially vulnerable ones. The place and role of the robot vis-à-vis the teacher can be questioned: as we see it, the role of the robot within the classroom (or at the therapist's clinic) does not infringe upon the role of the adult (teacher or therapist). The core of the learning by teaching

paradigm relies on the child becoming the teacher of an underperforming pupil (the robot): from that perspective, the robot does not replace the teacher; on the contrary, it plays a different role in the classroom, which happens to be novel as well: the robot is the least performing student and still a very patient, always eager to improve, one. In our experience, the teacher/facilitator retains an instrumental role during the interaction, and the learning would hardly occur if the child is left alone (or even semialone). The initial feedback that we received from the teachers during the focus groups confirms this perception: once explained, our approach makes sense to them and is welcomed as a relevant pedagogical innovation.

The implication of the mentor-protégé relationship on the children is less clearly understood. We have certainly seen that the children can establish strong affective bonds with the robot (as witnessed, for instance, by the letter sent by Vincent several months after he interacted with the robot), but we are not yet able to precisely characterize these bonds. The ethical implications of the mentor-protégé relationship have been explored before in the context of human teaching [8], [16], but they mostly looked at the question from the perspective of the protégé, whereas in our case, the child is the mentor. As such, relatively little is known about the psychological implications for a child to commit to helping a robot, and as advocated by Belpaeme and Morse [1], we likely need to first gain more field experience before being able to draw conclusions. Beyond handwriting, we do however believe that this work provides a novel perspective on the role for robots in the field of education. Learning by teaching is a powerful paradigm because of not only its pedagogical efficacy, but also its potential to positively impact the child's motivation and self-esteem. Although we need to carefully clear up the possible ethical concerns, we hope that this article shows that this is a very relevant context of the use for robots: when facing a child with school difficulties, robots can play the role of a naive learner that neither adults nor peers can convincingly play.

Acknowledgments

We warmly thank all the children who participated in the studies, the teachers, and the staff of the International School of Geneva, the Institut Florimont, and the Haut-Lac school for their support. We express our particular gratitude to Anne Gossin and Fanny Lebel for inviting us to their clinics. This research was partially supported by the Fundação para a Ciência e a Tecnologia with Grant No. UID/CEC/50021/2013 and by the Swiss National Science Foundation through the National Center of Competence in Research Robotics.

References

- [1] T. Belpaeme and A. F. Morse, "Time will tell—why it is too early to worry," *Interaction Stud.*, vol. 11, no. 2, pp. 191–195, 2010.
- [2] C. C. Chase, D. B. Chin, M. A. Oppezzo, and D. L. Schwartz, "Teachable agents and the protégé effect: Increasing the effort towards learning," *J. Sci. Educ. Technol.*, vol. 18, no. 4, pp. 334–352, 2009.
- [3] D. Gouaillier, V. Hugel, P. Blazevic, C. Kilner, J. Monceaux, P. Lafourcade, B. Marnier, J. Serre, and B. Maisonnier, "The NAO humanoid: a combination of performance and affordability," *CoRR*, arXiv:0807.3223, 2008.
- [4] J. Han, "Robot-aided learning and *r*-learning services," in *Human-Robot Interaction*, D. Chugo, Ed. Rijeka, Croatia: InTech, 2010, ch. 17. doi: 10.5772/8143
- [5] D. Hood, S. Lemaignan, and P. Dillenbourg, "When children teach a robot to write: An autonomous teachable humanoid which uses simulated handwriting," in *Proc. IEEE 2015 ACM Human-Robot Interaction Conf.*, Portland, OR, pp. 83–90.
- [6] M. M. P. Hoy, M. Y. Egan, and K. P. Feder, "A systematic review of interventions to improve handwriting," *Can. J. Occupat. Therapy*, vol. 78, no. 1, pp. 13–25, Feb. 2011.
- [7] A. Jacq, S. Lemaignan, F. Garcia, P. Dillenbourg, and A. Paiva, "Building successful long child-robot interactions in a learning context," in *Proc. IEEE 2016 ACM Human-Robot Interaction Conf.*, Christchurch, New Zealand, pp. 239–246.
- [8] W. B. Johnson and N. Nelson, "Mentor-protégé relationships in graduate training: Some ethical concerns," *Ethics Behav.*, vol. 9, no. 3, pp. 189–210, 1999.
- [9] S. Lemaignan, F. Garcia, A. Jacq, and P. Dillenbourg, "From real-time attention assessment to 'with-me-ness' in human-robot interaction," in *Proc. IEEE 2016 ACM Human-Robot Interaction Conf.*, Christchurch, New Zealand, pp. 157–164.
- [10] S. Lemaignan, A. Hosseini, and P. Dillenbourg, "PYROBOTS, a toolset for robot executive control," in *Proc. IEEE 2015 RSJ Int. Conf. Intelligent Robots and Systems*, Hamburg, Germany, 2015, pp. 2848–2853.
- [11] D. Llorens, F. Prat, A. Marzal, J. M. Vilar, M. J. Castro, J. C. Amen-gual, S. Barrachina, A. Castellanos, S. España, J. A. Gómez, J. Gorbe, A. Gordo, V. Palazón, G. Peris, R. Ramos-Garijo, and F. Zamora, "The UJIpencars database: a pen-based database of isolated handwritten characters," in *Proc. Sixth Int. Language Resources and Evaluation (LREC'08)*, Marrakech, Morocco, 2008.
- [12] A. Matsui and S. Katsura, "A method of motion reproduction for calligraphy education," in *2013 IEEE Int. Conf. on Mechatronics (ICM)*, Vicenza, Italy, 2013, pp. 452–457.
- [13] K. Mülling, J. Kober, O. Kroemer, and J. Peters, "Learning to select and generalize striking movements in robot table tennis," *Int. J. Robot. Res.*, vol. 32, no. 3, pp. 263–279, 2013.
- [14] C. A. Rohrbeck, M. D. Ginsburg-Block, J. W. Fantuzzo, and T. R. Miller, "Peer-assisted learning interventions with elementary school students: A meta-analytic review," *J. Educ. Psychol.*, vol. 95, no. 2, pp. 240–257, 2003.
- [15] J. Saunders, C. L. Nehaniv, and C. Lyon, "Robot learning of lexical semantics from sensorimotor interaction and the unrestricted speech of human tutors," in *Proc. 2nd Int. Symp. New Frontiers Human-Robot Interact.*, Leicester, United Kingdom, 2010.
- [16] W. J. Shore, T. Toyokawa, and D. D. Anderson, "Context-specific effects on reciprocity in mentoring relationships: ethical implications," *Mentoring and Tutoring: Partnership in Learning*, vol. 16, no. 1, pp. 17–29, 2008.
- [17] F. Tanaka and S. Matsuzoe, "Children teach a care-receiving robot to promote their learning: Field experiments in a classroom for vocabulary learning," *J. Human-Robot Interaction*, vol. 1, no. 1, 2012.
- [18] J. Werfel, "Embodied teachable agents: Learning by teaching robots," in *Proc. 13th Int. Conf. on Intelligent Autonomous Systems*, Padova, Italy, 2013.

Séverin Lemaignan, CHILI Laboratory, École Polytechnique Fédérale de Lausanne, Switzerland. E-mail: severin.lemaignan@plymouth.ac.uk.

Alexis Jacq, CHILI Laboratory, École Polytechnique Fédérale de Lausanne, Switzerland and Instituto Superior Técnico, University of Lisbon, Portugal. E-mail: alexis.jacq@epfl.ch.

Deanna Hood, CHILI Laboratory, École Polytechnique Fédérale de Lausanne, Switzerland. E-mail: deanna.m.hood@gmail.com.

Fernando Garcia, CHILI Laboratory, École Polytechnique Fédérale de Lausanne, Switzerland. E-mail: fernando.garcia@epfl.ch.

Ana Paiva, Instituto Superior Técnico, University of Lisbon, Portugal. E-mail: ana.paiva@inescid.pt.

Pierre Dillenbourg, CHILI Laboratory, École Polytechnique Fédérale de Lausanne, Switzerland. E-mail: pierre.dillenbourg@epfl.ch.

