Learning and understanding human skill

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Research results in machine learning have confirmed the possibility of reconstruction of human skill, resulting in similar or even improved performance of the same skill by a computer program. The methods that build symbolic models of skills are preferred if generated models are to be used to help humans in improving their own skill. The paper discusses these possibilities with the objective of accelerating and enhancing the process of human skill development. Experiments in learning control of dynamic systems are presented and wider potential of applications in assisting learning of skill is discussed.

1. Introduction

In many areas, professionals solve problems and perform tasks using highly specialized skills, acquired and accumulated through the years of experience. Examples can be found in almost every profession, such as piloting aircrafts, deciding in business dilemmas, diagnosing patients, operating cranes, etc. Development of computer science and informatics, especially in the field of intelligent systems, offers support to expert problem solving in many aspects, providing help in unusual cases, in achieving required reliability, in optimizing resources and meeting other specified success criteria. Still, learning human skill, including inevitable learning by doing (and making mistakes), remains a time-consuming and in some cases a very expensive process where appropriate computer applications could contribute to great improvements.

It has been shown experimentally that people have problems when trying to describe their performance of a task that requires skills. Their descriptions are not only incomplete and inaccurate, they can even differ from the facts that can be revealed from the recordings of their performance (Urbančič and Bratko, 1994a). This can be explained by the fact that skills become more or less subconscious when they develop to a satisfactory level of performance. Consequently, also teaching skills is difficult. It is not always clear what are the essential elements of skill that make somebody an outstanding performer, and trying to pass this knowledge to a learner and expecting him or her to apply it in their own performance is even harder. The phenomenon relates to the experience of brothers Wright, observing birds when looking for a solution for a technical detail in constructing their airplane a hundred years ago. In a book by Ferguson (1993), their experience is described as reported by Orvile Write: "Learning the secret of flight from a bird was a good deal like learning the secret of magic from a magician. After you once know the trick and know what to look for, you see things that you did not see when you did not know exactly what to look for."

To help learners and teachers involved in learning of skills, modeling of human skills could play an important role in the future. It is important that such a method captures current strategy at the conceptual level as well as important details critical for successful task performance. It must also allow for comparing models of teacher's and learner's skill, as well as the models of the learner's skill in different learning stages. It is easier to use such a model in the learning process if it is written in a formalism close to the human understanding of the problem. Therefore, in this context, we are not interested in subsymbolic learning methods such as neural networks, although it is known that in many cases, they can successfully model human skill.

Several studies have shown that symbolic machine learning methods can reconstruct human skill, generating a transparent model of human skill from traces of human performance (Michie et al. 1990, Sammut et al. 1992, Urbančič and Bratko 1994a). In all mentioned cases, the modeled skill was manual control of dynamic systems. Resulting decision trees can mimic the performance, recorded in traces that served as learning examples for the computer program. A detailed presentation of these studies with the emphasis on their limitations was published in

(Bratko and Urbančič 1997). An essential improvement of the approach was introduced by Šuc and Bratko (2000). In their work, Šuc and Bratko greatly enhance the relevance of the learned models in terms of human conceptualization by introducing goals and subgoals as typical elements of human problem-solving.

In Section 2, different types of knowledge are discussed and distinguishing characteristics of skill as a special type of knowledge are described. Section 3 presents experimental results in human learning of manual skill in dynamic system control and gives characteristics of this process in two series of experiments: one with a computer simulator and one with a physical model of a container crane. Findings of these experiments are used in Section 4 that discusses wider potential of modeling of human skill in helping humans to learn skills better and faster.

2. Types of knowledge

In everyday speaking, we use the word "knowledge" in very different contexts, without being aware of its multiple meanings. Different layers of knowledge become visible when it is applied in a repetitive mode in a well-known environment, in a changed environment, or in completely new circumstances, connected to other pieces of knowledge and leading to a new understanding of a whole or even to discovering new knowledge.

Classical science and philosophy have been discovering and studying propositional knowledge, which can be expressed and described in a propositional form, i.e. in sentences. Classical definition of propositional knowledge, introduced already by Platon, consists of three necessary and, when being together, sufficient conditions: it should be grounded, truthful and convincing. Since science functions at an intersubjective level, it should be grounded on basic facts, recognized by a scientific community as foundations of a certain field.

Although in science and education we do not cover only systematic and methodic explanations of different phenomena, this remains a basic goal that enables also achieving other goals, like solving problems in natural, social and technical areas. Answers to the "What" and "How" questions are important as well, although they are not necessarily systematically connected to the global tresury of scientifically accepted knowledge. In this sense, Ryle (1978) distinguishes between "knowing *that*" and "knowing *how*", being convinced that not all knowledge can be represented as propositional knowledge.

A typical example of "knowing *how*" is any example of a skill that somebody has developed through a long lasting period of performance, including learning that typically involves at least some trial and error process, and results in a more or less subconcious performance of the task. Such skills can be found in everyday life, like riding a bycicle or driving a car, or as parts of highly specialized professional tasks in various fields, ranging from operating cranes to piloting aircrafts or diagnosing in medicine. When asking a well-skilled performer for explanation, how does he or she actually perform a specific task which involves skills, they have difficulties in finding words for a description. They are typically not aware of all of their reactions, and even if they are, they can hardly give satisfactory details and explanations for them. It is much easier for them to manifest their skill by performance itself. As described in (Michie 1986), "know *how*" could be seen as a recognizing motto of skills, while "show *how*" could be used for their external manifestation.

Through a repetitive performance of a certain task, people develop a way of performing that has proven to be successful to a satisfactory extent, and they change it only if they are forced to do so due to changed circumstances or requirements. If we can describe such a way of performing in a reasonable way, we can talk about the *strategy*, which enables also better insight into the skill. This contributes to at least some exchangeability, giving us the possibility of talking about the strategy, discussing it with other people, and finally, using it in an educational process to help teachers and learners to make learning of skills more efficient.

3. Learning of skills

At the Jožef Stefan Institute, several series of experiments in learning skills were carried out in the domain of dynamic systems control. They cover

- experiments in which a computer program learned to control a dynamic system by a trial-and-error (Urbančič and Bratko, 1994b; Filipič et al., 1999), without a priori knowledge or with partial knowledge about the domain,

- experiments in which volunteers developed their human skill which was then used to produce learning examples for machine learning programs (Urbančič, 1994; Urbančič et al., 1998).

Results of exhaustive experimentation with machine learning, described in the publications mentioned in the previous paragraph, have confirmed that

- a computer program can learn to control a dynamic system without prior knowledge,
- a table of state/action rules as an encoded control rule can be compressed into a comprehensible control rule,
- a compressed comprehensible rule can be optimized, keeping all the qualitative characteristics of the strategy, but improving performance by setting quantitative details differently,

- qualitative knowledge about the domain can be used to shorten the process of learning, replacing the phase of learning without prior knowledge.
- traces of human performance can be used to shorten the process of learning, replacing the phase of learning from scratch.

Figure 1 shows how the mentioned modes of learning can complement and upgrade each other.

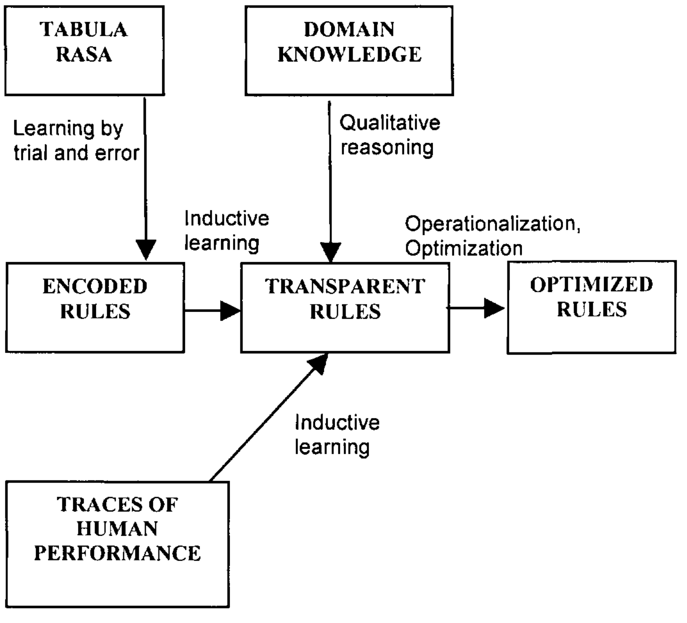

Figure 1: Different types of knowledge and learning can be used in learning skills and building their models.

We are further interested if the same repository of methods and techniques can help humans in learning their own skill. With this question in mind, in this paper we explore on the experiments where the emphasis is on observing human unsupervised learning of skill by trial and error and on the influence of transparent rules in form of verbal advice on this process. Knowing that a model of human task performance can be learned automatically from traces of performance, the idea is to use them together with other techniques (e.g. visualization, discussion) to help learners to develop their skill better and faster. In this paper we concentrate on the problem of transferability by studying to which extent and under what conditions a model of a skillful performer can help other learners that are still in the process of developing the same skill.

3.1. Learning to control a computer simulator of a dynamic system

Six volunteers participated in an experiment where they were asked to learn to control the crane simulator. They were given just the "instrument" version without any information about the system they controlled. They even didn't know it was a crane. The precise definition of the control task was as follows. By striking the keys ←, →, ↑ and ↓, bring the height of the six columns, representing state variables, within a narrow target region marked on each column. By striking the control keys, control variables presented in two additional columns change their value. The system is supposed to be stabilized at the target position, when all the six state variables stay within the target region for at least 8 seconds. The task is to stabilize the system as fast as possible. A trial is unsuccessful, if any of the six variables falls out of the specified boundaries (also marked) as well as if after three minutes the system is not stabilized within the target region.

Each subject was asked to perform 200 trials with the simulator. This amounted to roughly 8 to 10 hours of training for each subject. In order to develop their own control strategies, they were unsupervised and were not allow to observe other subjects' learning during this phase of the experiment. The whole learning process of the subjects was recorded, including the very first, unsuccessful trials.

After 200 performed trials, all the six subjects succeeded to accomplish the task they were given. While one of them still felt very uncomfortable and unsure, the others believed that they knew adequate control strategies. However, remarkable individual differences were observed regarding the speed of controlling and the frequency of successful experiments and the characteristics of the strategy used. Although observing when successful trials appear gives some basic information about the learning process, this is not sufficient to help subjects or their teacher. For example, they can warn that somebody is currently not making a progress, but they don't tell us why. Is the learner just not sufficiently attentive or concentrated or is it due to the fact that the learner builds an incorrect strategy? If yes, which elements of his or her current understanding should be corrected? Maybe the learner is building a promising strategy (maybe even a novel one, not yet known to the teacher), but needs more time to develop it? The problem is even harder in the domains where tasks can be performed in different ways. For example, in controlling cranes, some subjects tend towards fast and less reliable operation, while others were slower, more conservative, and more reliable. Some are avoiding large angular accelerations at the expense of time. Such strategies produce reliable, but slow performance. This is in contrast with some subjects' strategies that tend to achieve better times, but require higher accelerations whitch causes large angles and requires very delicate balancing at the end of the trail. To which extent individual characteristics could be respected and when one should try to change them?

To tackle this kind of questions, we need a better insight into a strategy that underlies a subject's current performance and represents his or her current understanding of the problem. To get this insight, we invited the subjects to a discussion where they were expected to compare their strategies and get some information that could help them in further improvements of their performance. After the discussion, subjects were given additional 50 trials each, in order to see how the discussion and other subjects' instructions affected their control performance.

It turned out that, although being incomplete and vague, the instructions formulated during the discussion provided useful guidance for some subjects. During the additional 50 trials, 2 volunteers significantly improved their performance. E.g., while in the first series of trials subject A had the best result of 75.64 seconds, after the discussion he achieved 56.84 seconds. Also his average improved, from 136.77 seconds to 120.20 seconds. It is interesting that his strategy on qualitative level remained the same, and he explicitly reported that his improvement was due to the one single numerical detail he didn't know before. On the other hand, subject B who didn't develop a consistant strategy during the first 200 trials, didn't improve at all. Even more, the subject reported about a confusion when trying to mix her way of performing with somebody else's instructions. This highlights the limited value of general verbal advice and confirms the importance of knowing which piece of advice is to be given to a particular subject at his/her specific stage of performance level. If it is given too early, the learner can not attach it to his or her current partial understanding. On the other hand, if it is given too late, the learner can already be very fixed in his or her way of performing the task which is therefore very difficult to be changed.

3.2. Learning to control a physical model of a crane

To study learning of control skill in a more realistic environment, in further experiments we used a physical model of a container crane. The functional part of the model consists of six sensors and two step motors. The motors are used to control the horizontal position of the trolley and the vertical position of the load. The inclination of the rope that carries the load is measured by an angle sensor mounted on the trolley. There are five other sensors, mounted on the construstion and used to detect the end positions of the track and the top and bottom positions of the load. The sensors and power electronics of the motors are interfaced with a computer program which is responsible for normal motor functioning, sensor data interpretation and control. The crane can be operated manually from the keyboard, as well as automatically by a computer program. Due to the importance of swing control, the study was focused on this part of the task. More precisely, the control task consisted of two subtasks: (1) increasing swinging from zero to a specified amplitude of 10 degrees, (2) damping swinging under a specified amplitude of 1 degree. Similarly to the objective in the experiments described in the previous section, the goal was to minimize the cumulative execution time.

Like in the experiments described in the previous section, also in this case a group of six volunteers learned to control the system by a series of unsupervised trials, with no communication among the subjects allowed. Each subject had 60 trials for the learning phase and 10 trials to exhibit the best possible performance. Basic characteristics of their learning process were seen from the graphs as the two given as an example in Figure 2. The dots represent time needed for each trial of a particular subject. Dots on the upper end of the diagrams represent unsuccessful trials while dots lying lower represent successful trials – the lower the better.

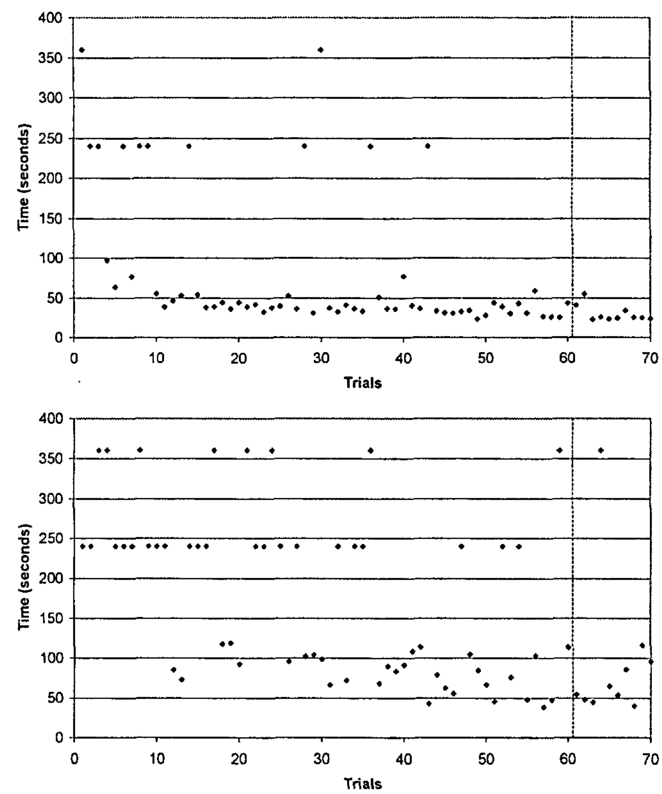

Figure 2: Basic characteristics of the learning process of two subjects, showing differences in learning speed, in number of unsuccessful trials and in time needed to accomplish the task in successful trials.

After the subjects had accomplished their task, the discussion with exchange of discovered features and advice took place, followed by additional 20 trials for each subject. Again, the goal was to observe the influence the discussion had on performans in the subsequent trials.

Based on the experience from the previous experiments where difficulties with wording of skill description revealed, in this case we used graphical presentation of qualitative characteristics of the skill (Figure 3) which was only in some details completed by quantitative information. Consequently, the process of describing and comparing the most distinguishing features of subjects' skill was much faster and easier.

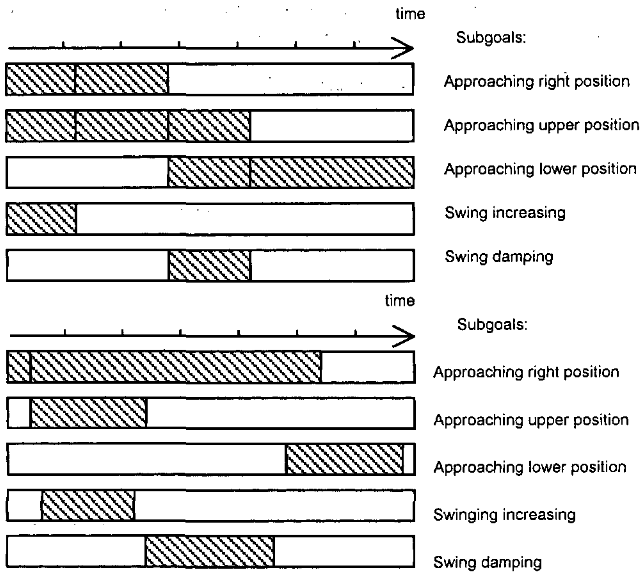

Figure 3: Basic qualitative features of control strategies developed by two subjects show differences in subgoal coordination.

Subjects reported on a point in the series of trials from which on "you know you will as a rule perform successfully". This is not necessarily the point when the first successful trial occurs. Differences in the speed of coming to this point were significant. Also differences in the subsequent improvement were big and not necessarily connected to the speed of progress in the initial phase of learning. In particular, a person that mastered the task relatively slowly, greatly improved in the continuation of the learning process and also ended up with a very reliable style of performing.

Experimental results reveal the same phenomenon as the ones with the numeric simulator, described in the previous section. While some of the subjects performed significantly better after the discussion, one improving the performance time by 13.5% and one by 20%, there was again a subject that could not improve at all. His comment was that he was obviously already too adjusted to the way of performance that he had developed.

4. Discussion

Presented experimental results could be briefly summarized by the fact that it is extremely important when to give a piece of advice to a certain learning subject, and which piece of advice should be given at a certain level of learner's understanding of the task. By intervening too early, learners can become confused since they have still not developed a model of the domain to which they could attach the told facts in a meaningful way. On the other hand, giving advice too late can result in necessarily big efforts needed first to "forget" already established control strategy that should be corrected, and then to develop a new one.

In any case, it is not sufficient to present the correct model of the skill to a learner, expecting him or her to adopt it and use it as his or her own. It is important to get some insight into the learner's current understanding and current stage of development of his or her own skill. Is it basically correct, but incomplete? Is it incorrect in some important features? What really counts is the comparison between the teacher's and learner's understanding. Different approaches that facilitate this understanding can be used, including discussion and simple visualization techniques. While the majority of the machine learning studies applied to the reconstruction of human skill concentrate of the problem of replicating the performance by a computer program, we believe that they have great potential as a modeling approach that could be used for enhancing the process of human learning in the domains where practice by trial and error is a necessary part of gaining needed experience.

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