Adapt2Learn: Designing Adaptive Physical Tools that Vary Task Difficulty Based on a Learner's Performance

We present adaptive physical training tools for motor-skills that automatically vary task difficulty based on a learner's performance. In contrast to feedback systems based on vibration or speech, our tools vary difficulty by physically adapting their shape. In two user studies with 25 participants, we show that automatically-adaptive tools lead to significantly higher learning gains when compared to static tools ($F_{1,11} = 1.856$, $p < 0.05$) and manually-adaptive tools ($F_{1,12} = 2.23$, $p < 0.05$). We provide an algorithm that automatically converts performance data into adaptation states for the tool while maintaining learners at the difficulty known as the 'optimal challenge point'. To help designers build adaptive tools, we present a user interface for generating adaptation code based on our algorithm that can be uploaded onto the tool's micro-controller. We then demonstrate how our algorithm and UI generalize across various tools for motor-skill learning by building 15 prototypes of adaptive tools.

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1 PROJECT SUMMARY

Research in learning has shown that when teachers personalize the training based on a learner's performance, it leads to higher skill acquisition [2]. This applies not only to skills, such as math and languages, but also to sports were it leads to higher motor skill acquisition [8]. However, such personalized training comes with an inherent limitation: *it does not scale*, and thus only a minority of learners get access to such improved training.

To make personalized training more scalable, and hence more accessible, training systems are needed that automate the steps a trainer takes to optimize the training for each individual learner. Among other interventions, trainers optimize training by *(1) providing feedback on the task execution* and *(2) adapting the task difficulty level* based on the learner's performance [4, 12]. While much research has been done to automate both steps for the learning of knowledge skills, such as math and languages, researchers have only started to investigate how to automate these steps for the learning of motor skills.

Motor skill training systems so far have mainly focused on automatically *providing feedback on the task execution* based on a learner's performance. They accomplish this by monitoring the learner's body when performing the motor skill and then providing either visual [11], vibrotactile [1, 9], or audio cues [6]. For instance, De Kok et al.'s system [3] uses motion capture to monitor how a learner performs squats and then provides speech-based feedback to improve the learner's posture. However, while these systems *provide automated feedback*, the issue of how to effectively *adapt task difficulty automatically* based on a learner's performance needs further exploration.

In motor skill learning, task difficulty can be adapted in several ways. Consider the example of learning how to play basketball: Scoring a basket can be made easier or harder by either *instructing*

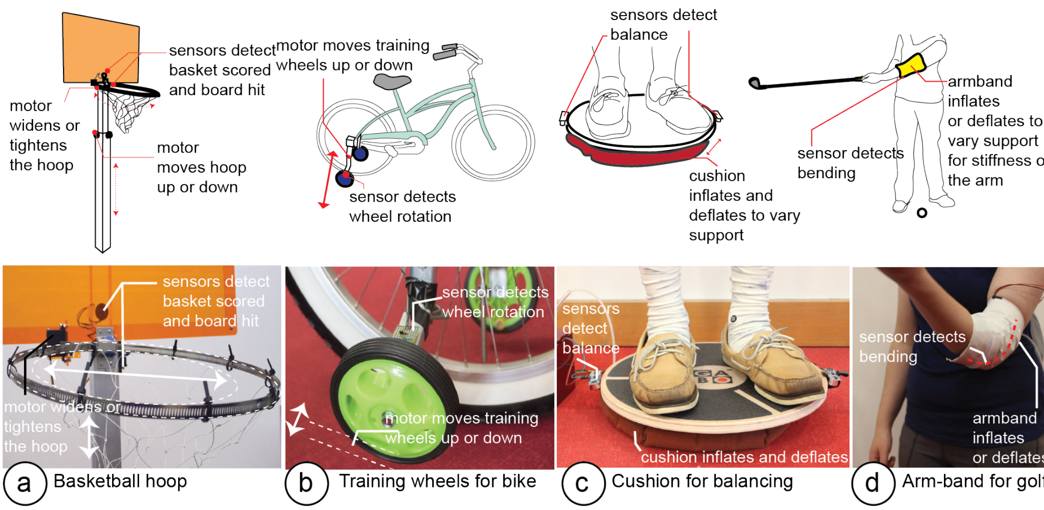

Fig. 1. Adaptive training tools adjust the task difficulty according to the learner's current performance: (a) Adaptive basketball hoop that can be widened/tightened and raised/lowered. (b) Adaptive training wheels for a bike that can be raised/lowered. (c) Wobbleboard with inflatable/deflatable support cushion to increase/decrease stability. (d) An inflatable/deflatable golf arm band that increases/decreases restriction when bending the elbow.

the learner to step closer or further away from the basket, or by *adapting the physical tool*, i.e. lowering or raising the basket or increasing or decreasing the hoop size [7, 10]. Since instruction based variations (e.g., 'step closer to the basket', 'step further away from the basket') can be created using existing multi-modal feedback mechanisms, such as speech, we focus our work on exploring the adaptation of the physical tool as a new method to vary task difficulty automatically.

While today, trainers already adapt physical tools *manually* to change the task difficulty based on a learner's performance, such as raising or lowering the basket in basketball, having an expert trainer adjust the difficulty does not scale towards a larger audience as mentioned earlier. In our work, we therefore investigate how to build physically adaptive training tools that *automatically adapt task difficulty by changing their own shape*. For example, our adaptive basketball stand automatically lowers and raises the basket and increases or decreases its hoop size depending on the learner's current performance, making it easier or harder to score.

To decide when to adapt the tool, our adaptive task-difficulty algorithm determines if the learner is training at what is called the *optimal challenge point* [5]. When learners train at the optimal challenge point, the task is neither too hard nor too easy for the learners' current skill level, which helps learners to make optimal progress. To evaluate if our task difficulty algorithm when deployed on an adaptive physical tool indeed leads to an improved learning gain, we ran a user study that showed a significant effect in performance when compared to static non-adaptive tools ($F_{1,11} = 1.856$, $p < 0.05$).

In addition, while there exist a few manually adaptive training tools in the market, our second study shows that the adaptation needs to be automatic because of the mismatch between a learner's skill level and their assessment of the best task difficulty for training. Our results show a significant difference in performance between a manually-adaptive mode in which participants are in control of the task difficulty and an automatically-adaptive mode in which our algorithm controls the adaptation ($F_{1,12} = 2.23$, $p < 0.05$). Thus, while expert trainers are able to set the task difficulty at the

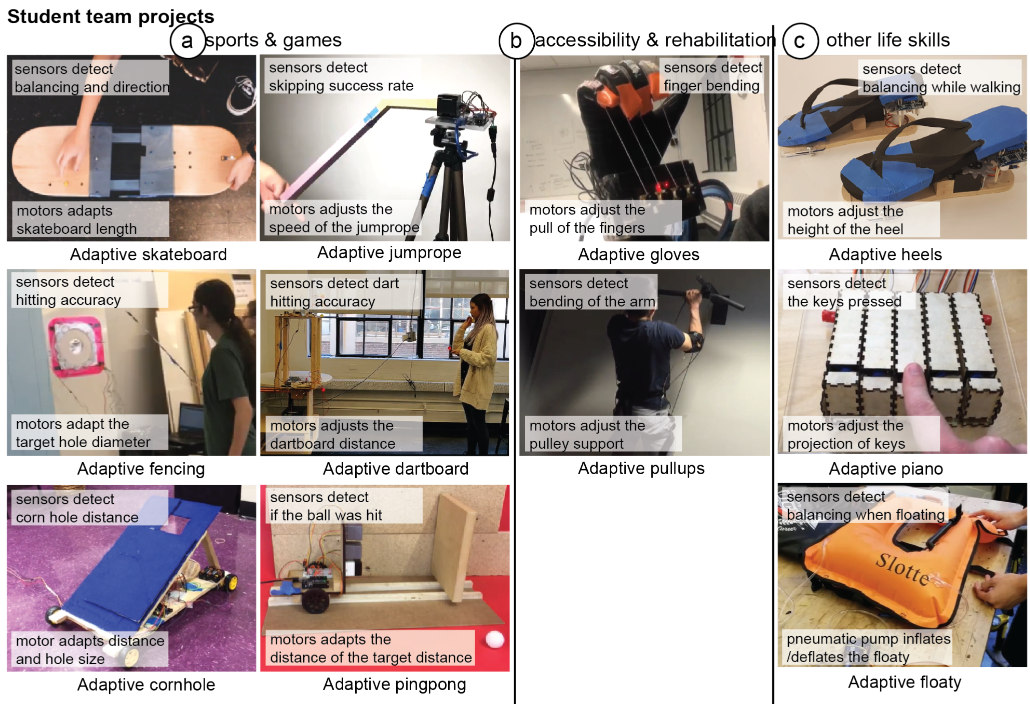

Fig. 2. Examples of adaptive training tools developed by students in a studio setting with applications in sports, health, accessibility and other life skills.

optimal challenge point for a learner, learners' when left on their own tend to either over-challenge or under-challenge themselves by training on a too high or too low task difficulty. In both cases, participants fail to maximize the learning potential that is achieved by setting the difficulty at the optimal challenge point.

To support designers in developing physically adaptive tools, we developed a user interface on top of our adaptation algorithm that allows designers to configure the sensors and actuators for training tools used in learning various motor skills. We demonstrate how this user interface helps to generalize our approach across a range of adaptive tools covering areas, such as basic life skills (biking), sports equipment (basketball, golf), and health support tools, such as those used in physiotherapy (e.g., wobble board). Besides the examples built by the research team and shown in Figure 1, we present an additional 11 prototypes built by students in a studio setting that further demonstrate the applicability of adaptive physical tools for motor skill training in a wide variety of different contexts ranging from sports and games, to accessibility and rehabilitation, and basic life skills (Figure 2).

2 RESEARCH QUESTIONS AND CONTRIBUTIONS

Our work is situated at the intersection of two research fields: the field of motor skill learning and the field of computational training tools. We take the concept of *varying task difficulty* from motor skill learning and implement task difficulty variation through *physical adaptation* in a set of computational training tools. We evaluate the benefits of such automated physical adaptation on performance after training and investigate how to generalize our approach across a variety of physical training tools.

In particular, we address the following two research questions:

1. Do adaptive tools that automatically vary task difficulty lead to larger learning gains than static or manually adaptive tools?

To answer this question, we proceeded as following:

- We conducted a user study with 12 participants to compare the learning gain when training on a *static* versus an *adaptive* physical tool. For this early study we used a naive adaptation algorithm that used a fixed encoding of performance to adaptation states. We chose basketball as the tool and throwing balls at the basket as the task for its short execution time and easy monitoring of success/failure states. Both the static and adaptive basketball setup were equipped with sensors to monitor the learner's performance. In the static condition, the basket height and hoop were fixed, whereas in the adaptive condition, the basket raised/lowered itself and the hoop automatically widened/tightened to adapt the task difficulty. Our results show a significantly higher learning gain in the adaptive condition when compared to the static condition ($F_{1,11} = 1.856$, $p < 0.05$).

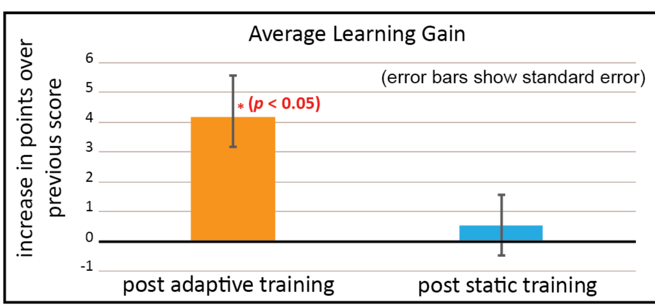

Fig. 3. User-study 1: Average learning gain post adaptive training and post non-adaptive training. The average learning gain post adaptive training is significantly higher than performance post static training ($F_{1,11} = 1.856$, $p < 0.05$).

- While we found significant differences in learning gain among the static and adaptive conditions, a post-hoc analysis between the two groups of participants showed that only those participants that trained on the adaptive setup first had a significant learning gain after training with the adaptive tool, whereas the learning gain when training with the adaptive tool was not significant for the group that trained on the static condition first. We thus concluded that while the results are promising, there is room for further improvement of the algorithm. Inspired by related work in motor-skill learning, we revised our naive algorithm to instead built on the concept of the optimal challenge point in motor-skill learning.
- After deploying the new algorithm on the basketball prototype, we conducted a second user study with 13 participants, in which we compared the learning gain of a *manually-adaptive tool*, in which participants selected a task difficulty level themselves versus an *automatically-adaptive tool*. We used the same basketball prototype but in the manually-adaptive condition, learners manually selected the hoop diameter and basket height whereas in the automatically-adaptive condition our algorithm determined those settings. Our results show a significantly higher learning gain in the auto-adaptive mode when compared to the manually-adaptive mode ($F_{1,12} = 2.23$, $p < 0.05$). We conducted a post-hoc analysis of our data and this time found an increase in learning gain independent of the order of conditions in which participants had trained.

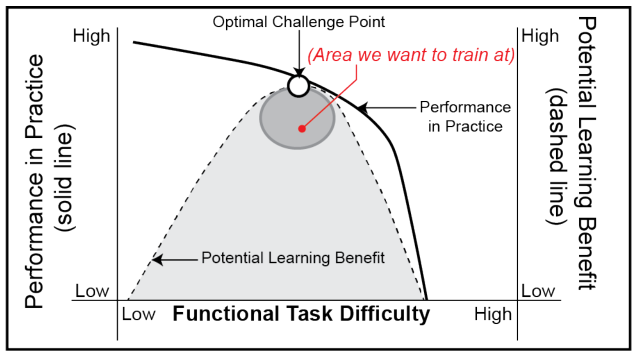

Fig. 4. The optimal challenge point is the level of functional task difficulty at which the task is neither too hard nor too easy, which allows for the largest potential learning benefit. Figure adapted from Guadagnoli et al. [5].

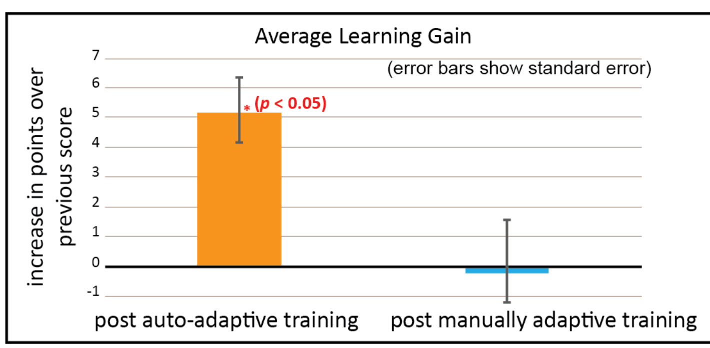

Fig. 5. User study 2: Average learning gain of post auto-adaptive and manually-adaptive training. The average learning gain in performance post auto-adaptive training is significantly higher than the performance post manually-adaptive training ($F_{1,12} = 2.23$, $p < 0.05$).

2. How can we facilitate the creation of automatically adaptive training tools that vary task difficulty?

After we demonstrated that automatically adaptive training tools, such as an adaptive basketball hoop, lead to a larger learning gain, we address the challenge of helping designers create such adaptive training tools themselves, which will facilitate follow-up studies on various training tools in the future. In particular, we focus on how to support designers in configuring the task-difficulty algorithm to work with the specific sensing and actuation of each tool.

- We built a user interface that takes as input the tool-specific sensing and actuation, as well as what determines a successful and failed attempt, and outputs a micro-controller script that designers can upload onto their training tool, thereby making it adaptive. The script computes the correct mapping of the sensor readings to actuation required at every stage of the training to maintain the difficulty level at the optimal challenge point. We demonstrate how this user interface generalizes across different adaptive tools by using it to configure the adaptation scheme for six prototypes: an adaptive bike, wobble-board, armband for practicing a golf-swing, skateboard, piano, and heels.

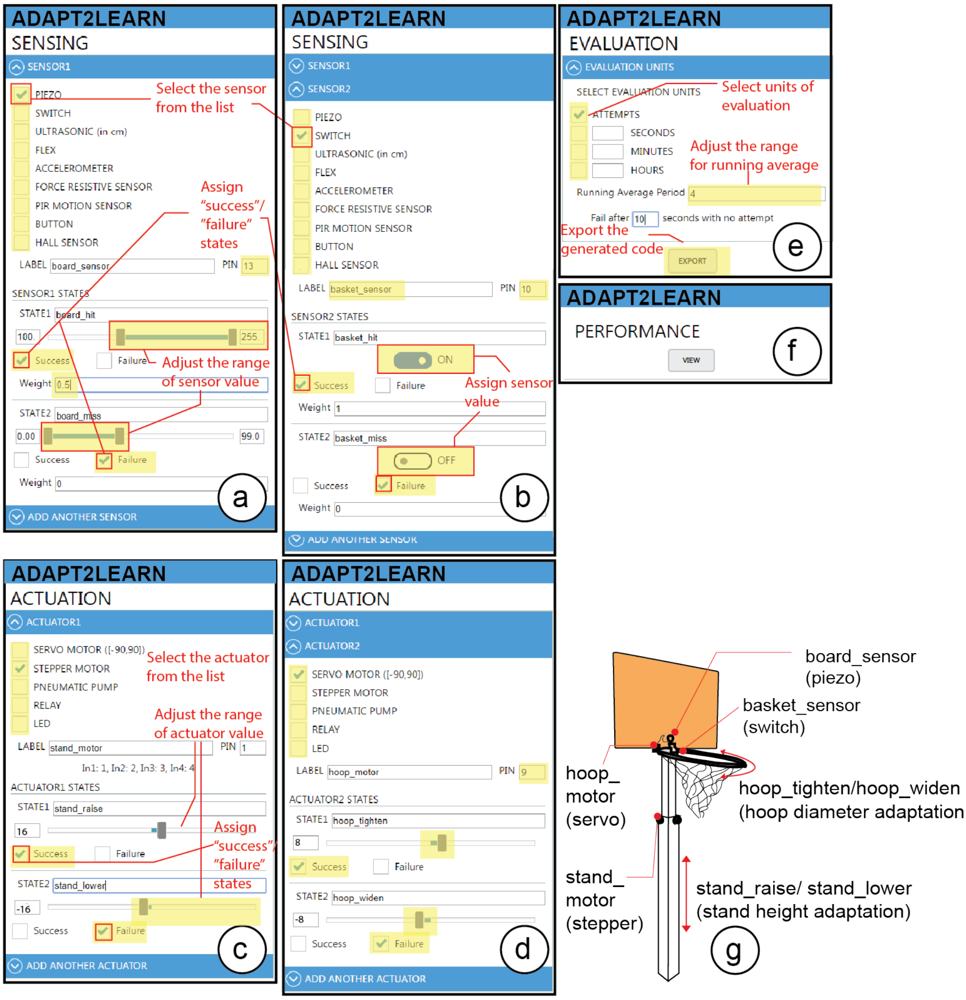

Fig. 6. Configuring the Adaption Scheme Using our UI: (a,b) registering sensors and mapping sensor data onto success/failure states and corresponding scores, (c) defining the performance evaluation unit and running average period window, (d,e) register actuators and indicate for each adaptation states how much to actuate, then (f) export the micro-controller script that was automatically generated. (g) The adaptive tool for reference.

- In addition, we built a visualization tool that displays the task difficulty level and underlying sensor and actuation data to further provide tool designers with insights into the adaptation process. Designers can use the visualization tool to cross-validate that the task-difficulty is maintained at the optimal challenge point during training and can see how each learner is progressing from beginner to expert.
- Finally, we conducted a studio-design class in which 25 student teams were asked to design and build adaptive tools for learning motor skills to demonstrate that our approach is applicable beyond prototypes build by the research team and to gain further insights into the design space of physical adaptive tools.

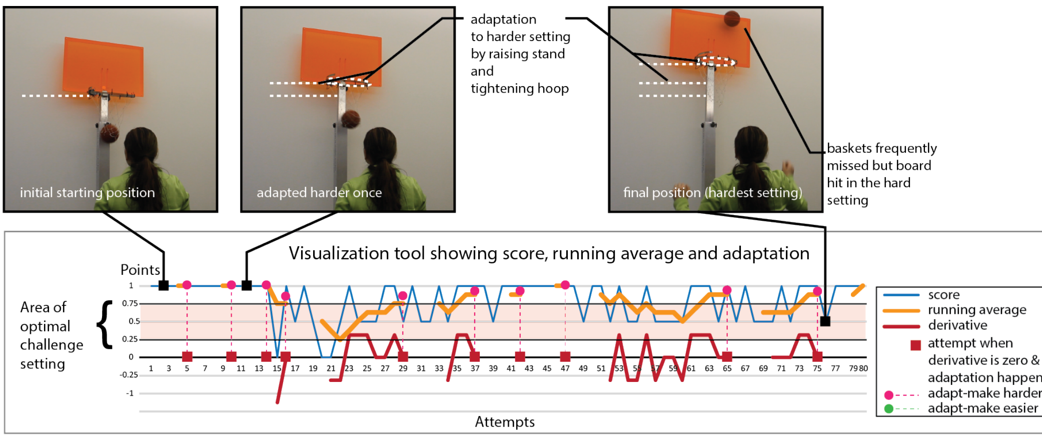

Fig. 7. Visualization of the scoring of a learner (p7 from the user study) and the adaptation frequency over a number of attempts. As seen in the graph, the tool adapts to the next harder setting when the the performance plateaus (i.e., when derivative of the running average is zero) and when the score is high, which implies that the learner has mastered that level of difficulty.

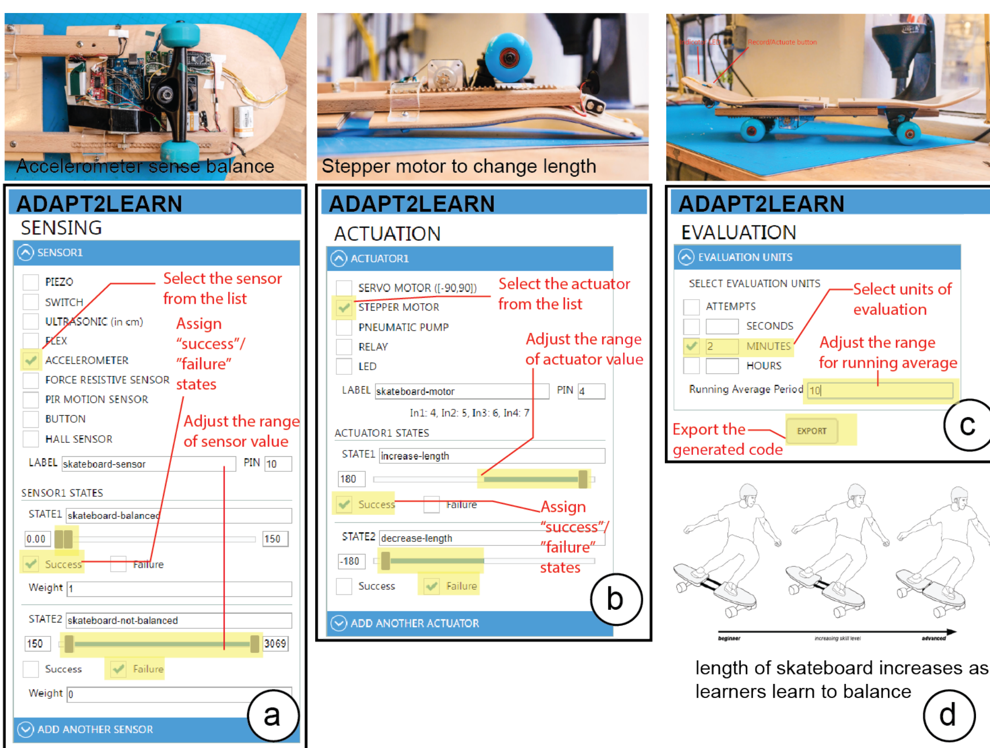

Fig. 8. Adaptive skateboard: (a) accelerometers sensors to measure balance, (b) stepper motor as actuator, (c) configure the evaluation window and generate the Arduino code for adaptation. (d) Concept design for reference.

Contributions:
In summary, we contribute:

- a new approach to vary task difficulty in motor-skill learning through automatic physical adaptation of the training tool;
- two user studies with a total of 25 participants demonstrating the benefits of automatic-adaptive tools over static and manually-adaptive tools, both leading to significant increases in performance ($F_{1,11} = 1.856$, $p < 0.05$ and $F_{1,12} = 2.23$, $p < 0.05$);
- the development of a task-difficulty adaptation algorithm that maintains the optimal challenge point for a learner when a physically adaptive tool is used;
- a user interface that allows designers to configure the task-difficulty algorithm for tool-specific inputs/outputs and that generates a micro-controller script that can be deployed on the adaptive training tool;
- a visualization tool that demonstrates that the tool adapts to keep the task difficulty at the optimal challenge point for the learner and that helps trainers to gain insights into where the learner is in the process of transitioning from beginner to expert;
- a total of 15 adaptive physical training tools (4 built by the research team and 11 built by student teams in a studio setting) demonstrating that our adaptation algorithm and user interface can be generalized for applications in sports, rehabilitation, and every-day life skills.

We start by summarizing the related work to provide additional background information on existing feedback and task difficulty systems for motor skills learning, and then detail each part of our contributions throughout the paper in the order described above.

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