Using 3D Printing and Actuation to Adapt Physical Tools to Facilitate Motor Skills Learning

Dishita Girish Turakhia, Yini Qi, Lotta Blumberg, Kevin Reuss, Stefanie Mueller
MIT CSAIL, Cambridge, MA, USA
{dishita, qyn, blumberg, kreuss, stefanie.mueller}@mit.edu

ABSTRACT
Many motor skills that people learn throughout their lives involve mastering a physical tool, such as riding a bike, writing with a pen, or playing basketball. To reduce the level of difficulty, learners use physical learning aids, such as training wheels for a bike, that provide physical support. To date, these learning aids only come in predefined levels: For instance, training wheels are either mounted or taken off. This jump from beginner to expert level makes the transition difficult for learners.

In this paper, we address this challenge by adapting the physical tool according to the learner's progress. For instance, while learning to ride a bike, we monitor learners' balancing skills and as they improve, we gradually lift the training wheels to reduce support and increase the difficulty. Thus, our approach enables a step-by-step transition from beginner to expert level that, similar to existing adaptive learning systems for math and language skills, is personalized for each individual learner.

To illustrate our idea, we built an end-to-end system that allows designers to setup adaptable tools that physically change when a learner's skill level increases. Our system uses sensors integrated with the tools to measure progress; parametric 3D modeling to adapt the tool; and then either actuation or refabrication to deploy the physical change.

Author Keywords: personal fabrication; adaptive learning.

ACM Classification Keywords: H5.2 [Information interfaces and presentation]: User Interfaces.

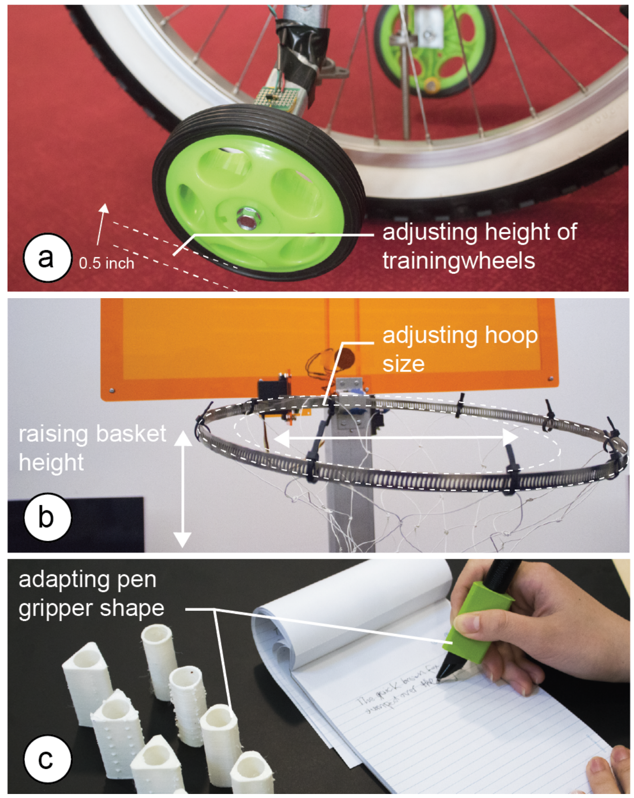

Figure 1: We adapt the physical tool according to the learner's progress: (1) Riding a bike: as learners' balance improves, we gradually reduce support by lifting the training wheels off the ground. (b) Basketball: we widen the hoop for beginners and tighten the hoop as they learn to score baskets. (c) Writing: we provide easy-to-hold triangular grippers for beginners and gradually change the shape to cylindrical as learners improve their grip.

INTRODUCTION

Adaptive learning systems (ALS) aim to achieve an optimal learning curve by allowing every learner to learn with their own personalized system made specifically for their strengths, weaknesses, and learning pace [23]. To accomplish this, ALS continuously monitor the learner's performance and adapt the level of difficulty of the task based on their progress. ALS have been implemented extensively in online education. For instance, the *DreamBox* [5] learning system tracks students' performances and adjusts the level of difficulty, number of hints, and pacing as appropriate.

Recently, researchers have taken the concept of adaptive learning from the realm of learning math and language skills, and applied it to the learning of *motor skills.* By monitoring the learner's body while performing the motor skill, these systems provide feedback to improve the accuracy of execution. For instance, De Kok et al.'s system [26] uses motion capture to monitor how a user performs squats and then provides personalized speech feedback to improve

submission to *ACM UIST 2018*

different aspects of the user's posture, such as the neck angle and amount of knee bending.

Many motor skills that people learn throughout their lives involve mastering a physical tool, such as riding a bike, writing with a pen, or playing basketball. To help learners master these skill, physical learning aids are used to decrease the level of difficulty. For instance, when learning how to ride a bike learners tend to start out with training wheels that provide additional support to make up for their imperfect balance. Similarly, when learning to write, grippers are used to help learners learn the correct grip.

Unfortunately, today, these physical learning aids only exist in pre-defined steps and do not adapt to the learner's individual progress (Figure 2a): For instance, training wheels are either mounted or taken off, and pencil grippers are provided as a fixed set of attachments, such as one for beginners, intermediates, and close to experts.

In this paper, we propose to apply the concept of adaptive learning to mastering physical tools, i.e., to provide physical learning aids that adapt their level of difficulty to enable the learner to make optimal progress (Figure 2b).

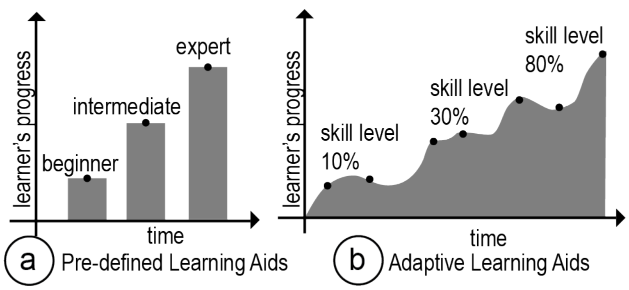

Figure 2: (a) Traditional physical learning aids exist in pre-defined steps. (b) In contrast, we gradually adapt the learning aid according to the learner's progress.

RELATED WORK

Our work is related to research that investigates how to improve motor-skills using sensors and multi-modal feedback. We classify this body of work into: (1) motor-skills that do not require physical tools, such as dancing and running, and (2) motor-skills that involve physical tools, such as skate-boarding, golfing, and archery. We refer to Santos et al.'s survey [22] for in-depth analysis.

Motor Skills Without Physical Tools (Dancing, Running)

A range of systems use sensors to monitor a learner's progress. *Saltate*! [9], for instance, is a dance system that uses force sensors under the learner's shoes to sense the timing of each dance step and provide feedback on rhythm. Lee et al.'s system [12] measures swimmers' arm strokes on entry and exit of the water using IMUs on the arm. Bloomfield et al.'s system [4] helps learning karate by using a motion capture system to analyze wrist rotation and elbow position. Portillo-Rodriguez et al.'s Tai-Chi [21] learning system also uses motion capture but adds visual and audio feedback via a virtual reality system and stereo-speakers. *Runright* [16] helps improve learner's running style using accelerometer data from the learner's phone. *FootStriker* [9] takes this concept further by using electric muscle stimulation to actuate learner's foot muscle into the right position. Besides sport applications, sensor-based systems have also been used in rehabilitation. For instance, *Sit-to-Stand* [15] helps stroke patients relearn the transition from sitting to standing by using accelerometers to measure balance and provide feedback using vibration.

Motor Skills with Physical Tools (e.g., Golfing, Archery)

Existing systems that support learning of motor skills that require mastering a physical tool use the same sensing and multimodal feedback approach as described in the previous section. The *Motion Log SkateBoard* [18], for instance, uses a pressure-sensor matrix on a skateboard deck to measure a learner's foot position, pressure intensity, and timing of foot movements. The *Copy Paste Skate System* [20] extends this by exploring different feedback mechanisms, such as replaying the audio of a trick, vibrating the floor, and visualizing the skateboard path. The *Motion Echo Snowboard* [19] also uses a pressure sensor to sense weight distribution but displays it using LEDs matrices on the board. *Learning Archery* [8] uses an accelerometer and gyroscope to measure unwanted tilting of the bow. *TapTrain* [24] supports roller skates derby players by using an accelerometer to measure crossovers and strides. Marchal-Crespo et al.'s tennis training system [13] uses a VR cave and provides force feedback on a tennis racket. *Kelly et al.'s* [11] system supports users in learning golf by using motion capture and a virtual avatar. Ghasemzadeh et al. [7] also tackle golfing but attach IMUs to both the golf club and the learner's upper body to capture swing performance. *SwingSound* [17], finally attaches an accelerometer to the club and replays the swing to the user through audio. Baca et al.'s [2] and Blank et al.'s [3] systems help train for table tennis by measuring spin, position, and where the ball hits the table. Finally, the *rowing* [1] system records ground reaction forces as well as the pulling force using a force transducer on the chain of a rowing ergometer. Besides sports training, systems have also been developed for other areas that include physical tools, such as music. For instance, *MusicJacket* [10] helps learners learn how to play the violin by providing vibration feedback on their posture.

ADAPTING PHYSICAL TOOLS

The main contribution of this paper is the idea to go beyond multi-modal feedback with vibration and speech and to incorporate the *adaptation of the physical tool* into the learning process.

Adaptation Pipeline

Figure 3 illustrates how we integrate tool adaptation into the existing *sense, map, feedback* pipeline of systems mentioned in the related work: (a) *Sensing:* Similar to the systems in the related work, we track the learner's current performance using different sensors based on the motor skill being learned. (b) *Mapping:* we then analyze the sensor data, measure learners' progress and map the progress onto the corresponding change for the physical tool. (c)

Feedback: In contrast to the related work, we do not support the learner by using multi-modal feedback, but instead by adapting the physical tool. We achieve this adaptation by either actuating the tool (e.g., using motors) or refabricating parts of the tool (e.g., via 3D printing).

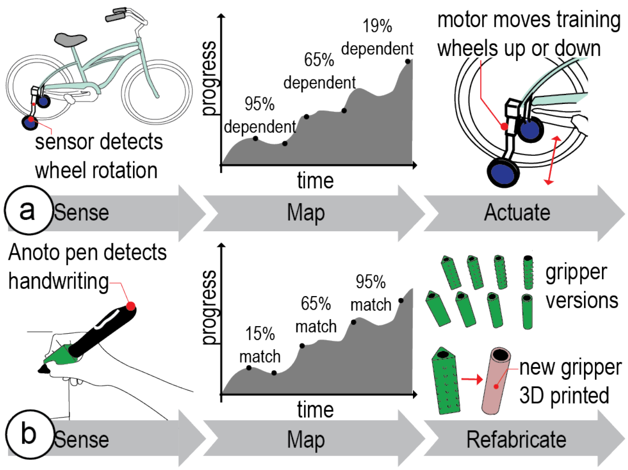

Figure 3: The sense-map-adapt pipeline we used for all examples in this paper. For adaptation, we either (a) actuate the physical tool, or (b) refabricate it.

Note that our work does not replace existing multi-modal methods but provides additional ways to facilitate learning. For instance, in the case of learning how to ride a bike it might be beneficial to both adapt the training wheels and to provide speech or vibration feedback on how to change the body posture to improve balance.

WALKTHROUGH: LEARNING HOW TO BIKE

To realize this *sense, map, adapt* cycle, we built an end-to-end system that maps sensor data onto a parametric 3D model of the tool before deploying the physical change. In the next section, we illustrate this system using the example of the bike with adaptive training wheels.

Sensing the Learner's Performance

To monitor learner's balancing skills, we measure the amount of time the training wheels are in contact with the ground while riding. If the learner is balancing the bike well, the training wheels do not make contact as they are in a slightly raised position off the ground [25]. They only make contact when the learner is leaning too far to the left or to the right and risks falling. Thus, the lesser the time the training wheels are in contact with ground, the better the learner's balancing skills are.

To detect when the wheel touches the ground, we mounted hall effect sensors close to the training wheels and attached magnet to the wheels (Figure 4): When the wheel touches the ground, it rolls, and thus rotates the magnet with it. When the magnet is parallel to the hall effect sensor, the voltage read from the sensor is lowered. The sensor is wired to an Arduino that streams the sensor data via Bluetooth to our main application.

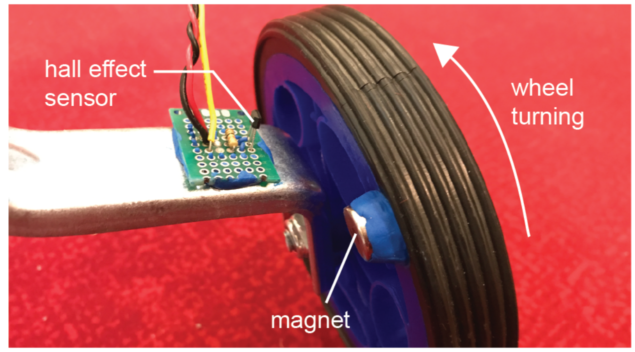

Figure 4: A hall effect sensor on each training wheel measures how much the learner is relying on it.

Analyzing Data & Changing the Parametrized 3D Model

The main application is implemented using *Grasshopper* as a plugin for the 3D editor *Rhinoceros*. Our application visualizes the current state of the bike in the form of a 3D model (Figure 5a). The adaptable parts of the bike, i.e. the training wheels, are setup as parametrized parts and highlighted in red.

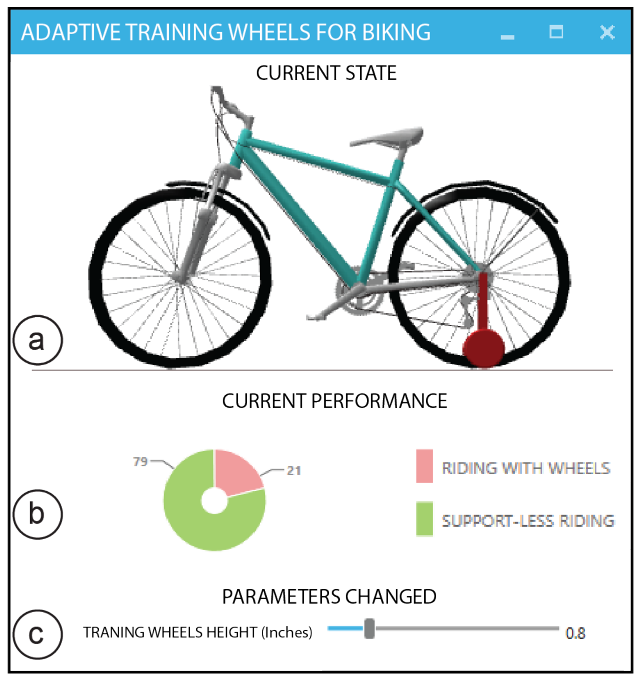

Figure 5: (a, b) When the support wheel sensor readings indicate a new level of expertise, (c) the support wheel height parameter of the training wheels changes, which updates the parametric 3D model accordingly.

When the sensor data from the magnetic sensor indicates a change in skill level, the *height* parameter of the training wheels in the 3D model updates to increase or decrease the difficulty level. Once the 3D parameter is updated, the training wheels in the 3D model are lifted or lowered accordingly.

Adapting the Physical Tool

The change in the parametric 3D model is then send via Bluetooth to its corresponding physical tool (i.e., the bike). This causes the motors attached to the training wheels to lower or lift them into the correct position (Figure 6).

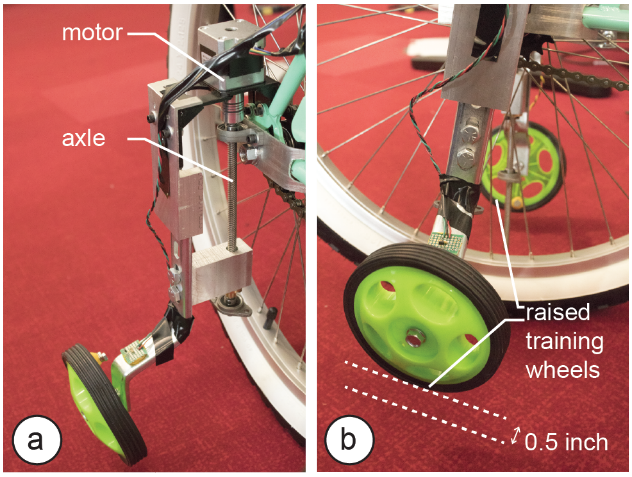

Figure 6: Motors on the training wheels lift or lower them according to the learner's current progress.

DESIGNING ADAPTABLE TOOLS

We designed the adaptive tools illustrated in this paper by addressing the following points:

(1) What *aspect of the overall skill* is being learned?

(2) What *type of physical support* reduces the difficulty level for this skill while ensuring learning?

(3) How can *the tool be changed* to provide this support?

For biking, the aspect of the skill being learned is balancing. The physical support that reduces difficulty for balancing are the training wheels at varying heights from ground. The most effective method to implement the physical change is to use of motors to lift / lower the wheels.

Question 1 and 2 target *aspects of learning* and thus are best answered by domain experts, such as coaches of a specific skill. Because it is beyond the scope of this paper to provide a full study of every example, we do not claim that our prototype implementations provide the optimal way to realize learning for the specific skills. Rather these examples serve as proofs of concept for applications of our system in different domains.

Question 3 targets *aspects of tool design* and thus requires engineering knowledge for setting up the parametric 3D model and building the physical mechanism. In this paper, we take the role of the tool designer by choosing the sensors, setting up the parametric model, and implementing the mechanism for physical change.

In the following, we describe the procedure we adopted to setup one of the examples of our adaptive learning tools.

#1 Aspect of Skill Being Learned & #2 Type of Support

Consider the example of golf, in which learners first have to master the correct swing and hit position of the ball on the club (aspects of skill being learned).

The type of physical support that reduces the difficulty for these skills are the shaft length and loft angles of the club face: In general, clubs with shorter shafts are easier to use because the short length results in better control. Similarly, higher loft angles are easier to use since they make it easier for the club to sweep from underneath the ball. As a result, shorter clubs and higher loft angles are used to first help beginners learn how to swing and hit the ball. Only later on, longer clubs with lower angles are used by expert users to hit higher distances.

We use this information to create the initial design of the club, i.e. we create a parametrized 3D model of it with parameters shaft length and loft angle (Figure 7). Our adaptive tool thus can be changed by varying either the shaft length parameter or the loft angle parameter.

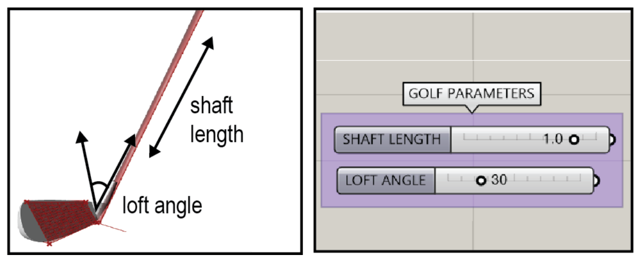

Figure 7: Parametric 3D model of the golf club.

This setup also enables changing a single parameter at a time while keeping the others constant (Figure 8a). In contrast, the traditional approach that uses sets of pre-defined tools typically changes multiple parameters simultaneously (Figure 8b). For example, in the traditional approach in Figure 8b, the medium difficult version of the golf club changes both the shaft length *and* the loft angle, even if the learner only has mastered one of the two. Our parametric 3D model, in contrast, allows us to change each aspect of the tool individually (e.g., making the shaft longer but keeping the loft angle the same, see Figure 8a). This enables users to progress on one subskill while not being overly challenged on the other weaker subskill.

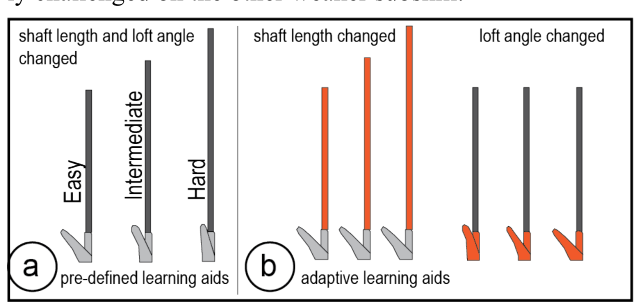

Figure 8: (a) Pre-defined existing tools change multiple parameters at once even if the learner has only mastered one of them. (b) In contrast, with our system we can adapt each parameter individually.

In the next step, we set up the sensors on the golf club. First, we decided which sensors to use. For this, we interviewed a golf coach at our home institution who informed us that hitting position and hit impact on the club face are two key characteristics to determine when to progress the learner to next level of difficulty. Both, the impact and the hit position, can be sensed using a pressure sensor array mounted on the front face of the club (Figure 9). With the sensor in place, we use both the sensor data and the parametric model to setup the conditions for when the physical tool should adapt.

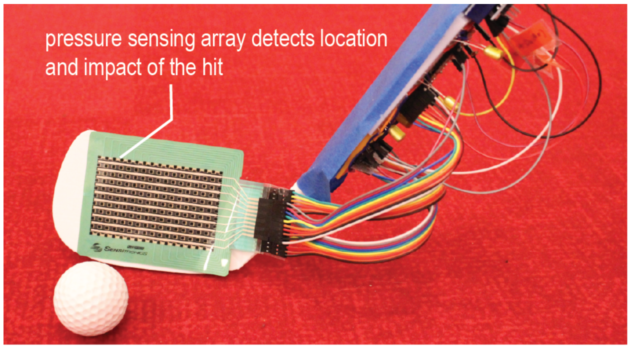

Figure 9: Adaptable golf club prototype with pressure sensor array to determine hit location and impact.

#3 How to change the physical tool?

In the final stage of tool design, we have to investigate how to change the physical tools effectively. We considered two methods: (1) actuation, and (2) re-fabrication. We base the choice of physical adaptation method on the response time and kind of adaptation required.

A faster response time enables a *tight feedback loop* between the learner's progress and the adaptation of the physical tool. By using actuation with motors in the bike example, the lifting of the training wheels is an immediate response to the learner's increase in skill level. Refabrication, in contrast, takes more time and thus comes with a slower feedback loop, but can be used for learning tasks that take a longer time to learn. Alternatively, reprinting a tool partially, such as only replacing the front face of the golf club, or reprinting small tools, such as the pencil grippers from Figure 1c, can be done in less than one hour.

On the flipside, refabrication is more versatile than actuation since it can produce physical tools of very different shapes, weights, and materials. Actuation has limitations because every physical adaptation requires additional electronic and mechanical components to be integrated with the tool. Such integration gets significantly harder for small physical tools, such as the pencil grippers, that do not offer sufficient space for housing the components. In this case, adapting through reprinting proves to be the more efficient mechanism.

As both approaches have trade-offs, we use actuation mainly for one-dimensional changes, such as moving a training wheel along an axle as in the bike example, and refabrication for more complex changes, such as adapting the shape of the front face on the golf club (Figure 10).

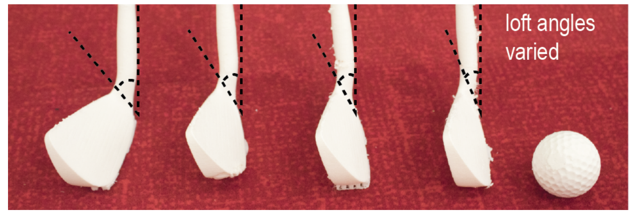

Figure 10: Printed golf club faces with different loft angles.

ASPECTS OF ADAPTABLE PHYSICAL TOOLS

In the previous section, we presented a step-by-step description for developing a new adaptable learning tool. In this section, we will discuss additional design considerations.

Physical Tool and Peripheral Tools

After surveying different kinds of motor skills, we found that in some cases, the physical tool consisted of multiple parts. For instance, golfing does not only include handling the golf club (the main tool), which exists in different versions but also the ball. Beginner balls, for instance, tend to be lighter and larger than the expert ball and learners slowly transition towards being able to handle more weight. We call these additional set of tools the *peripheral tools* (Figure 11). Similarly, the gloves in golfing can be used to facilitate learning: While products, such as the *SensoGlove* [28], provide vibration feedback on the learner's grip the glove itself remains the same and does not facilitate handling the tool, for instance, by providing more or less friction.

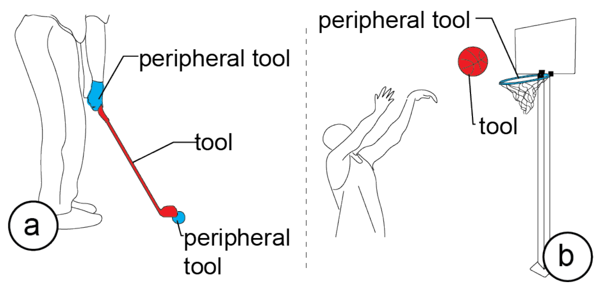

Figure 11: Tools and peripheral tools for (a) golf and (b) basketball.

Similarly, in basketball, the ball is considered the main tool and there are beginner and expert versions of the ball (lighter vs. heavier balls, smaller vs. bigger balls). The basketball hoop (considered as peripheral tool) can also be modified to facilitate learning by widening the hoop to increase the chances of scoring (Figure 11b).

Using our system, both the tool and these peripheral objects can be made adaptive: For golfing, our system allows to adapt both the club (shaft length, loft angle) and the ball (size, weight) to influence the impact of the swing as can be seen in Figure 12.

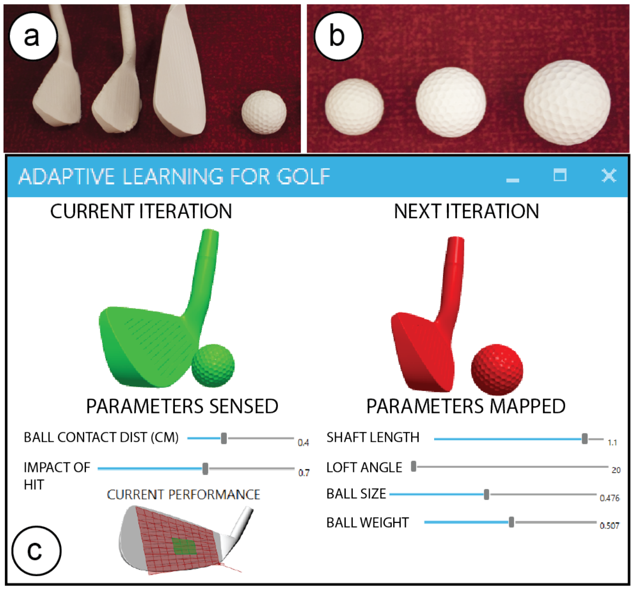

Figure 12: Adaptable golf club and ball (a) reprinted versions of club face (b) reprinted golf balls with different sizes and weights (c) golf UI.

Attachment vs. Integration of Learning Support

Second, we found that for some motor skills the physical support is an external *attachment* while for others the physical support is *integrated* with the tool itself (Figure 13). For instance, biking requires attaching additional training wheels and writing support requires additional grippers to be attached to the pen. In contrast, both golfing and basketball change the tools and peripherals itself, for instance, by using different front faces for the golf club and different sizes of the hoop (Figure 13b).

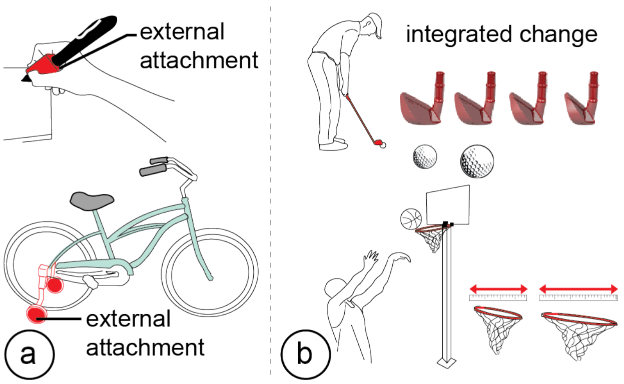

Figure 13: (a) External attachment vs. (b) tool integration.

We found that the decision about attaching the support vs. integrating it with the tool is based more on practical considerations rather than the learning aspect itself. For instance, pen grippers could potentially be integrated directly with the pen by replacing the pen's outer shell or using shape changing materials to change the pen's shape. However, because learners might use different pens, the external attachment provides the benefit of being usable for multiple different pens. These design decisions are important as they affect the subsequent sensing, parametrization, and adaptation of tool in the subsequent stages of the pipeline.

TYPES OF SUPPORT FOR LEARNING

In this section, we briefly highlight different types of physical support, such as those that guide users into the correct *position,* and help them with the correct *orientation* and *applied force.* We illustrate them with additional prototype examples.

Positioning Support: Finger Placement & Grip

Different learning aids exist to help learners properly position fingers, hands, and feet, in relation to the tool. For instance, writing with a pen requires mastering the correct finger and hand position to achieve a stable grip. Conventionally, pencil grippers attached to the pen are used to help learners master the correct grip style. Beginner level grippers are triangular shaped, i.e., they provide a flat surface for each finger and help practice the pinch grip. Advanced grippers are cylindrical and thus more difficult to grasp.

Figure 14 shows how we provide adaptive support by integrating this example into our sense, map, adapt pipeline. (a) We use Anoto digital pen to capture the learner's writing on paper. (b) Using computer vision, we calculate the recognizable percentage of the writing. (b) As the percentage increases, we 3D print a new version of the gripper that reduces gripping support, i.e., is roundish shaped. Since pencil grippers are small, printing a new writing aid only takes 30 minutes.

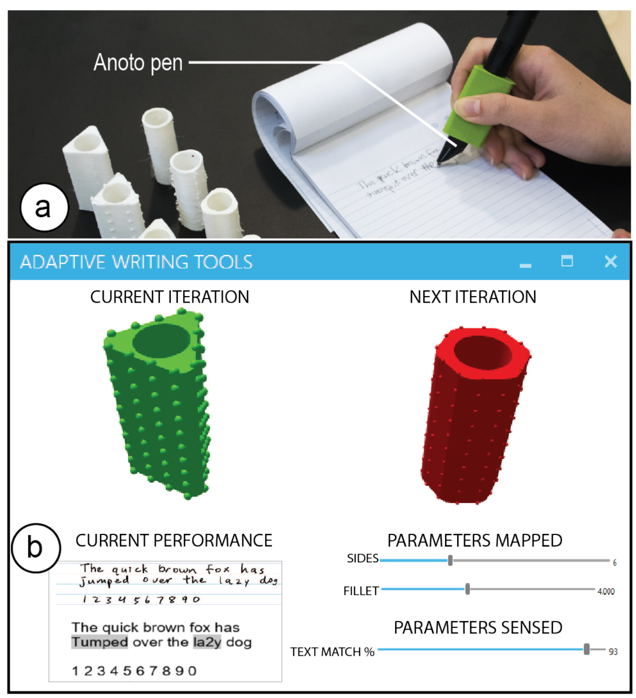

Figure 14: Learning the correct grip for writing: (a) writing captured with Anoto pen, (b) analyzing the recognizable writing, (c) adapting the gripper.

Orientation Support: Alignment & Targeting

A second aspect of motor skill to consider often includes mastering correct orientation, alignment and targeting. For instance, when learning to play basketball, learners have to correctly orient the ball according to the height of the basket—a task that gets increasingly harder the further the basket is away. Figure 15 shows a prototype we built for an adaptable basketball training setup that starts with the basket at a low height and wide hoop and then increasingly raises the basket and makes the hoop narrower as learner's improve in performance. A close up is shown in Figure 1b.

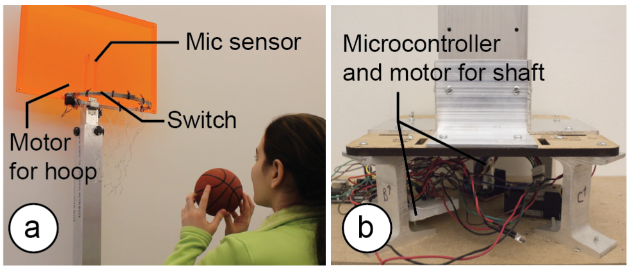

Figure 15: Basketball: (a) A motor widens/tightens the hoop, a contact microphone measures hits on the back plate, a switch on the net measures scoring. (b) A motor on the shaft lowers/raises the basket.

We sense the learner's current skill level by comparing how often the learner scores, hits the board and misses completely. To detect scored baskets, we connected a switch to the hoop net and mounted a contact microphone on the board to measure board hits. Figure 16 shows the corresponding parametric model and the sensor data.

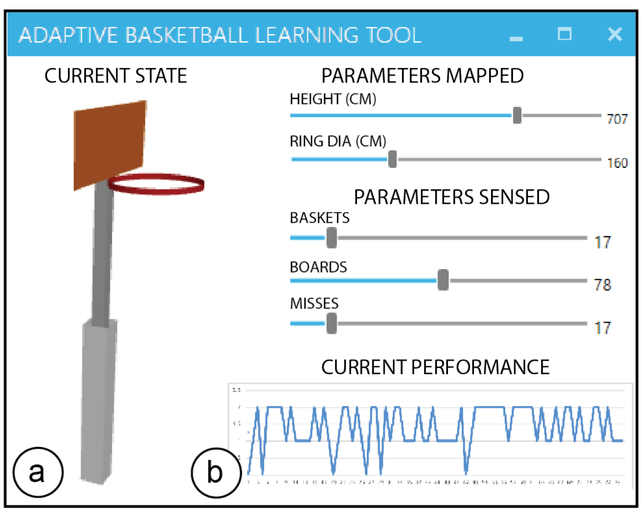

Figure 16: (a) Parametric model of the basketball. (b) Sensor data from the contact microphone & switch.

Applied Force Support

Finally, the applied force plays a major role in many motor skills with physical tools. For instance, in golfing, the impact on the ball has a substantial effect on how close or far the ball will reach. In our adaptive golfing prototype that we showed in Figure 12, we measure the impact of the swing using pressure sensor. By analyzing how far the ball reaches, we can change the shaft length, loft angle or weight to modulate the dampening effect.

IMPLEMENTATION

Although each physical tool requires its own custom implementation, such as the choice of sensors for measuring the learner's progress, we provide a generic pipeline that allows to quickly setup a new adaptable tool.

The software pipeline is illustrated in Figure 17 and reflects the three steps mentioned earlier: *sense, map, adapt.*

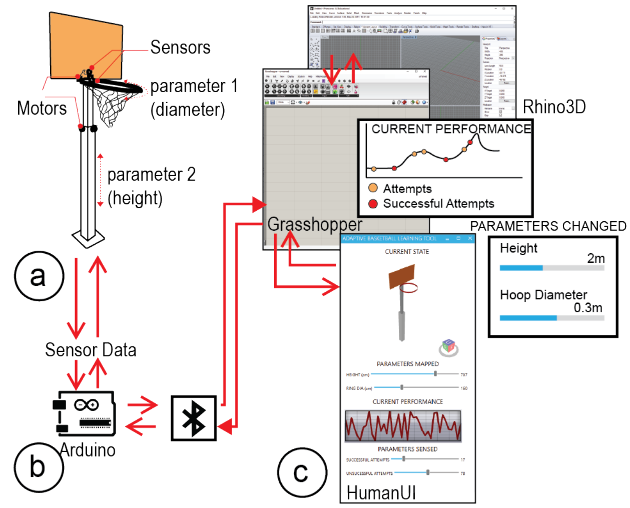

Figure 17: Software pipeline: (a) physical adaptive prototype with motors, (b) microcontroller and Bluetooth module to communicate with (c) the grasshopper interface and Rhinoceros 3D environment. (a) Parametric model of the basketball. (b) Sensor data from the contact microphone & switch.

Streaming Sensor Data to Main Application

Once the decisions for the choice of sensors, mapping and mode of adaptation is made, the designer first sets up the Arduino file. The Arduino file requires two functions to interface with our main system. The first function is the collectSensorData() function, which returns a list of all sensors and their current data values. For instance, in the basketball example, the function returns <(microphone, amplitude), (switch, on)>. The second function is the deployActuation() function, which takes in the actuator and its value. For basketball this list contains both motors values <(motor-hoop, timesteps), (motorbasket, timesteps)>.

Before sending the data to the main application, the Arduino script analyzes the data and decides which state the sensor data implies. For instance, in the basketball we threshold the audio signal received from the contact microphone on the board to determine if the board was hit or not. We then transfer the result via Bluetooth to a nearby computer that does the main processing.

Analyzing, Aggregating & Mapping the Sensor Data

The sensor output is then collected and analyzed in our main application. In the case of basketball, we receive data from two sensors, (i) the microphone on the board and (ii) the switch. If the switch was activated, we set the current state to 'basket', if the switch was not activated but the board was hit, we set the state to 'board', if the board also was not hit, we set it to 'miss. Next we record the performance and after every 4 attempts, deploy the change in ring diameter and height using the matrix shown in Figure 18.

		BASKETS				
		0	1	2	3	4
BOARD HITS	0	Ring big Height less	Ring big Height less	No Change	Height more	Ring small Height more
	1	Ring big Height less	No Change	No Change	Height more	
	2	No Change	No Change	No Change		
	3	Ring big	Ring big			
	4	Ring big				

Figure 18: Matrix for deploying change after every 4 throws for the ring/hoop diameter and height.

Updating the 3D Model & Deploying the Actuation

Once the decision on actuation is computed, the parametric 3D model is updated in the UI. The application also displays the updated height and hoop width.

Once the 3D model is updated, the updated height parameter is used to change the corresponding physical basketball stand. This change/adaptation is achieved by streaming the updated height data values back to Arduino via Bluetooth using the *deployActuation()* function as mentioned before. In the deploy function, the height parameter is then converted into a specific number of turns for the motor.

If the adaptation is achieved using re-fabrication, for example in the case of the pencil grippers, a new .stl file is saved every time the 3D model updates. The user can use this .stl file, to print the new version using a 3D printer.

CONTRIBUTIONS, BENEFITS, AND LIMITATIONS

We make two main contributions: First, we present the idea of building an adaptive learning system for motor skills that *adapts the physical tool*. Second, we implement this idea through an end-to-end system that uses a *sense, map and adapt* cycle to measure learners' performance, map it onto a parametric 3D model, and then deploys the physical change either through actuation or refabrication. We also built several prototypes to demonstrate the application of our end-to-end pipeline for a variety of learning tasks that involve physical tools, such as riding a bike, writing with a pen, and playing basketball.

We also conducted a user study to evaluate our idea and its application for learning basketball (reported in the next section). Our findings reveal that similar to existing adaptive learning systems used for learning language or math, our approach also has the potential to retain learners longer by alleviating early frustrations. As mentioned before, our approach is not a replacement of multi-modal feedback (vibration, speech) but provides an additional method to support the learner in the learning process.

Our system is subject to the following limitations: (1) *speed of adjustment:* While systems solely based on sensors and multi-modal feedback, such as vibrations and audio, can adapt in real-time, physical adaptation takes more time. Although physical change through actuation (e.g., via motors or shape changing materials) can be realized within a few seconds, more complex changes in the tool's shape require refabrication, which can take hours of printing time. (2) *Integration of sensors / actuators with the tool:* Adding sensors and actuators to the tool can potentially change how the tool functions. For instance, adding sensors to the golf club by simply attaching them to the front face and handle changes the clubs center of mass, which can affect the swing. Thus the sensor integration should be carefully designed for each tool. (3) *Mapping learning with adaptation:* For this paper, we mapped the sensor data to learning outcomes based on simple metrics. For future work, each of the physical adaptations should be carefully calibrated to map to each learner's progress.

USER STUDY

We conducted a user study with one of our prototypes to evaluate the learning gain achieved using our adaptive system vs. a non-adaptive system. We were also interested in the qualitative feedback and learning experience of the participants.

Learning Task: Basketball

For the study, we selected the basketball prototype to test with the users. The skill tested was throwing balls into the basket and we scored the performance as: successful baskets (score=2), at least the board was hit (score=0.5) and complete misses (score=0). We measured the learning gain by comparing performance scores before and after training sessions. Given the prototypes we had built for this paper, basketball was the best choice for user testing because the task took a relatively short amount of time (each throw took ~3-4 seconds), allowing us to collect more data points per participant within an hour of study. Each participant attempted 220 throws over 5 sessions: (i) skill assessment: 20 throws (ii) training condition #1: 80 throws (iii) post-training test: 20 throws (iv) training condition #2: 80 throws (v) post-training test #2: 20 throws.

Training Conditions:

Our study is based on prior study conducted to test the performance of throwing balls into buckets at varying distances[27]. We ran a within-subjects experiment i.e. the participants were trained in both adaptive and non-adaptive conditions but were randomly assigned an order. Participants were tested before and after each training condition on the same hardest setting. We recorded the scores and computed the training gain for each participant by comparing their before and after training condition scores. The two training conditions were:

Condition 1 Adaptive Setup: In this condition (Figure 15), participants started by throwing balls in the easiest setting, (lowest basket height and largest hoop size) and gradually progress to the harder settings. The physical change was deployed based on scores after every 4 throws based on the aforementioned chart in Figure 18, with 80 throws in total.

Condition 2 Non-Adaptive Setup: In this condition, participant attempted 40 throws for the easiest setting (i.e. largest hoop, lowest basket height) and then another 40 throws for the hardest setting (i.e., the smallest hoop and the highest basket height). We trained on both easiest and hardest setting for non-adaptive setup based on the precedent study we referenced above [27].

Hypotheses

Our hypotheses for the study were:

(1) Learning with an adaptive learning system will result in a faster learning gain, which is reflected in a higher performance score after the same amount of time when compared to the non-adaptive learning system.

(2) Learning with an adaptive learning system will maintain a steady difficulty level (which is just slightly above participant's current skill level) as opposed to the non-adaptive setup. This steady difficulty level will result in a higher motivation than learning with a non-adapting system.

We collected both quantitative data and qualitative feedback to evaluate our hypothesis.

Study Task

We conducted our study in six phases:

Phase 1: Calibration of Distance to Basket: Results from our pilot study showed that participant's height and prior skill determined their respective difficulty level. When placed at the same distance from the ring, a tall person found the hardest task easy and a short person would find easiest task hard. We found that these differences can be compensated by varying the distance to the basket for each participant. To start every participant with the same rate of success in the easy setup, we proceeded as following: Every participant starts with 12ft distance from the hoop and attempted 4 throws. If less than 2 throws scored baskets, then the participant moved 1ft closer and repeated the process. Once 2 or more throws scored the basket, the participant maintained that distance for the rest of the study. After calibration, 4 participants stood at 12 ft, 2 participants at 11ft, 2 participants at 8 ft and 1 participant at 10ft, 9ft, 7ft and 6ft each. (mean =9.8 ft, std. deviation = 2.07).

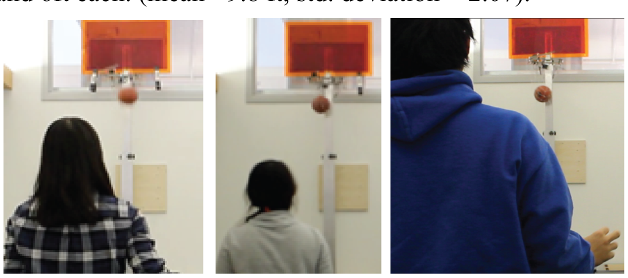

Figure 19: User Study Setup.

Phase 2: Pre-training skill assessment test: Next, the participants attempted 20 throws in the hardest setup. This test helped us assess the participant's pre-training skill level. We recorded the data on participant's performance (*scores, board hits, misses*) to be able to compute the training gain later on.

Phase 3: Training: In this phase the participant trained for 80 throws. We randomly assigned participants to either the adaptive condition first or the non-adaptive condition first.

Phase 4: Post-training skill assessment test: To measure the participant's learning gain after training with the first setup, we repeated task in the pre-training skill assessment test, i.e. participants attempted 20 throws in the hardest setting. Again, we logged the data to be able to compute the training gain later on.

Phase 5: Training with other: Each participant then trained with the other setup (i.e., the non-adaptive setup for those who trained in the adaptive setup first and vice versa).

Phase 6: Post-training skill assessment test: To measure the participant's training gain after training with the second setup, we again asked participants to attempt 20 throws in the hardest setting.

In all phases, we instructed participants to score as many points as possible and they were allowed to take as much time as they wanted. In total, the study took about one hour per participant, including a pre-study and post-study questionnaire.

Participants and questionnaire

We recruited twelve participants (8 female, 4 male) with ages between 18-31 years (mean=25, s=3.3) from our institution.

Results

As mentioned before, each attempt by the participant was recorded and scored as follows: successful *baskets* (score=2), at least the *board was hit* (score=0.5) and complete *misses* (score=0). Thus, an average value between 0.5-2 in a chart, such as the one in Figure 20, refers to a participant who mostly hit the board or scored, while an average value between 0-0.5 means that the participant mainly missed or only hit the board.

(1) Learning gain: We calculated the learning gain for both adaptive and non-adaptive training conditions, by comparing the test scores before and after that training session. We observed that post adaptive training, the participants scoring increased slightly compared to the post non-adaptive training period, but a t-test did not find a significant difference (p-value = 0.22).

(2) Difficulty and performance over time: As expected, in the *non-adaptive* condition, participants' performance dropped significantly as soon as they switched from the easiest to the hardest setting (Figure 20). In contrast, in the *adaptive* condition, participants' performance remained close to constant across all training samples even as the difficulty increased. These results align with our expectations as the system was designed to keep a constant difficulty level maintained for the participant.

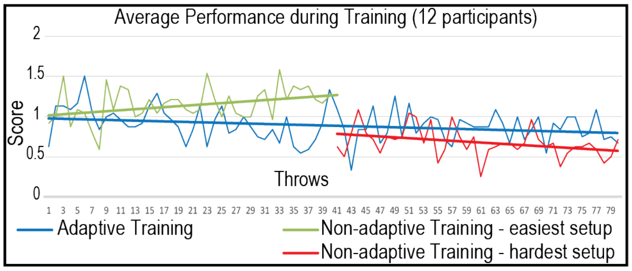

Figure 20: Average performance during adaptive training vs non-adaptive training. An average value between 0.5-2 in the chart refers to participants mostly hitting the board or scoring, while an average value between 0-0.5 means that participants mainly missed or only hit the board.

(3) Qualitative Feedback: When participants were asked if they would rather retrain with the adaptive or the non-adaptive setup, 8 out 12 participants preferred the adaptive setup. Following are some of the quotes written by participants when asked to highlight the benefits and drawbacks of each condition.

Seeing the physical tool adapt: 'Changes with the hoop was cool […] like having a personal trainer motivate me […] when it was getting tighter, I would think I'm doing good, when it got loose I would think I should do better' (p7). 'Adaptive training makes each stage of training experience more rewarding so it helped me focus better.' (p11) 'Adaptive mode let me see gradual progress, while non-adaptive mode just felt like either shots that were too easy or an exercise in futility.' (p8). 'The adaptive training made me reflect upon what I'm doing wrong by physically changing the height and hoop size (discouraging) and made me want to change my throwing style faster.' (p3) These comments show that getting immediate feedback on performance by seeing changes can be motivating when progress is made but also can be demotivating when the setup gets easier. This impact on emotions should be considered for future designs. For example, before getting easier, the setup could maintain its current state for a while.

Having adaptive difficulty levels: 'it's more natural! [...] it matches learning process better' (p7). 'adaptive mode felt more useful in slowly adjusting to let me get better at harder and harder shots' (p8). However, one participant also mentioned 'I prefer to be challenged beyond my current capability and learn that way.' (p10) Thus, for future work, it might be beneficial to set the adaptation stages to each participant's preferred level of challenge.

Variety of training vs. specific movements: Some participants stated that they might perform better by only practicing on the hard condition. 'I feel like I get better if I just practice with hard level and nothing else' (p5). '[while] adaptive training is more interesting, non-adaptive training helps me improve specific movements' (p4). While this hypothesis can be tested in the future, our referenced study shows that learners learn better when trained on variety of settings in comparison training on specific goal task [27].

CONCLUSION

In this paper, we presented a novel approach to help learners that are learning motor skills that involve a physical tool. We demonstrated that adapting the physical tool and thereby gradually transitioning from easy to hard can prevent learner's frustration in the early stages of the learning process. We illustrated our end-to-end system that uses sensors on the tools, parametric 3D modeling, and actuation/refabrication to change the amount of support provided to the learner. We provided a step-wise procedure for designing adaptive learning tools and gave an overview of different design considerations necessary during the process. Finally, we conducted a user study to evaluate learning gain using an adaptive system.

For future work, we plan to investigate other means of physical adaptation, especially those that promise fast but versatile changes. Potential directions include shape changing materials and meta-materials that can encode multiple material states in a single 3D print.

ACKNOWLEDGEMENTS

<removed for blind review>

REFERENCES

1. Arnold Baca and Philipp Kornfeind. Rapid Feedback Systems for Elite Sports Training. In *IEEE Pervasive Computing* 5, 4, 70-76, 2006.
2. Arnold Baca and Philipp Kornfeind. Real Time Detection of Impact Positions in Table Tennis. In *Engineering of Sport* 5, 1, 508, 2004.
3. Peter Blank, Thomas Kautz, and Bjoern M. Eskofier. Ball Impact Localization on Table Tennis Rackets Using Piezo-Electric Sensors. In *Proceedings of the 2016 ACM International Symposium on Wearable Computers* (ISWC '16), 72-79.
4. Aaron Bloomfield and Norman I. Badler. Virtual Training via Vibrotactile Arrays. In *Presence: Teleoperation and Virtual Environment* 17, 2, 103-120, 2008.
5. DreamBox: Adaptive, Online K-8 Math Education http://www.dreambox.com/
6. Dieter Drobny, Malte Weiss, and Jan Borchers. Saltate!: A Sensor-Based System to Support Dance Beginners. In *CHI '09 Extended Abstracts on Human Factors in Computing Systems* (CHI EA '09), 3943-3948.
7. Hassan Ghasemzadeh, Vitali Loseu, Eric Guenterberg, and Roozbeh Jafari. Sport Training Using Body Sensor Networks: A Statistical Approach to Measure Wrist Rotation for Golf Swing. In *Proceedings of the Fourth International Conference on Body Area Networks* (BodyNets '09). Article 2.

8. Heng Gu, Kai Kunze, Masashi Takatani, and Kouta Minamizawa. Towards Performance Feedback Through Tactile Displays to Improve Learning Archery. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers* (UbiComp/ISWC'15 Adjunct), 141-144.

9. Mahmoud Hassan, Florian Daiber, Frederik Wiehr, Felix Kosmalla, and Antonio Krüger. FootStriker: An EMS-based Foot Strike Assistant for Running. In *Proceedings of ACM Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 1, Article 2, 2017.

10. Rose Johnson, Janet van der Linden, and Yvonne Rogers. Real-time Feedback for Learning the Violin. In *Proceedings of the 25th BCS Conference on Human-Computer Interaction* (BCS-HCI '11), 535-538.

11. Philip Kelly, Aoife Healy, Kieran Moran, and Noel E. O'Connor. A Virtual Coaching Environment for Improving Golf Swing Technique. In *Proceedings of the 2010 ACM Workshop on Surreal Media and Virtual Cloning* (SMVC '10), 51-56.

12. J.B. Lee, B.J. Burkett, D.V. Thiel, D.A. James. Inertial Sensor, 3D and 2D Assessment of Stroke Phases in Freestyle Swimming. In *Procedia Engineering* 13, 148-153, 2011.

13. L. Marchal-Crespo, M. van Raai , G. Rauter, P. Wolf, R. Riener. The Effect of Haptic Guidance and Visual Feedback on Learning a Complex Tennis Task. In *Experimental Brain Research* 231, 3, 277-91, 2013.

14. Dennis R. Miaw and Ramesh Raskar. Second Skin: Motion Capture with Actuated Feedback for Motor Learning. In *CHI '09 Extended Abstracts on Human Factors in Computing Systems* (CHI EA '09), 4537-4542.

15. Craig O'Neil, Mark D. Dunlop, and Andrew Kerr. Supporting Sit-To-Stand Rehabilitation Using Smartphone Sensors and Arduino Haptic Feedback Modules. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (MobileHCI '15), 811-818.

16. Stina Nylander, Mattias Jacobsson, and Jakob Tholander. Runright: Real-time Visual and Audio Feedback on Running. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems* (CHI EA '14), 583-586.

17. Stina Nylander, Alex Kent, and Jakob Tholander. Swing Sound: Experiencing the Golf Swing through Sound. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems* (CHI EA '14), 443-446.

18. Hyung Kun Park, HyeonBeom Yi, and Woohun Lee. Recording and Sharing Non-Visible Information on Body Movement while Skateboarding. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (CHI '17), 2488-2492.

19. Hyung Kun Park and Woohun Lee. Motion Echo Snowboard: Enhancing Body Movement Perception in Sport via Visually Augmented Feedback. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (DIS '16), 192-203.

20. Sebastiaan Pijnappel and Florian 'Floyd' Mueller. Designing Interactive Technology for Skateboarding. In *Proceedings of the 8th International Conference on Tangible, Embedded and Embodied Interaction* (TEI '14), 141-148.

21. Otniel Portillo-Rodriguez, Oscar O. Sandoval-Gonzalez, Emanuele Ruffaldi, Rosario Leonardi, Carlo Alberto Avizzano, Massimo Bergamasco. Real-Time Gesture Recognition, Evaluation and Feed-Forward Correction of a Multimodal Tai-Chi Platform. In *International Workshop on Haptic and Audio Interaction Design, LNCS,* 5270, 2008.

22. Olga C. Santos. Training the Body: The Potential of AIED to Support Personalized Motor Skills Learning. In *International Journal of Artificial Intelligence in Education,* Volume 26, Issue 2, 730–755, 2016.

23. Derek H. Sleeman, John Seely Brown. Intelligent Tutoring Systems. *Academic Press,* eds., 1982.

24. Craig D. Stewart, Penny Traitor, and Vicki L. Hanson. I'd tap that!: Providing Real Time Feedback on Roller Derby Skills. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems* (CHI EA '14), 2221-2226.

25. Bikemanual:http://www.bike-manual.com/brands/trek/om/kids/training_wheels.htm

26. Iwan de Kok, Julian Hough, Felix Hülsmann, Mario Botsch, David Schlangen, and Stefan Kopp. A Multimodal System for Real-Time Action Instruction in Motor Skill Learning. In *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction* (ICMI '15), 355-362.

27. Kerr, Robert, and Bernard Booth. "Specific and varied practice of motor skill." *Perceptual and motor skills* 46, no. 2 (1978): 395-401.

28. Sensoglove. http://www.sensoglove.com/en/