

Adaptive Visualisations Using Spatiotemporal and Heuristic Models to Support Piano Learning

Jordan Aiko Deja
University of Primorska
Koper, Slovenia
De La Salle University
Manila, Philippines
jordan.deja@famnit.upr.si

ABSTRACT

Learning the piano is hard and many approaches including piano-roll visualisations have been explored in order to support novices in this process. However, existing piano roll prototypes have not considered the spatiotemporal component (user's ability to press on a moving target) when generating these visualisations and user modelling. In this PhD, we are going to look into two different approaches: (i) exploring whether existing techniques in single-target spatiotemporal modelling can be adapted to a multi-target scenario such as when learners use several fingers to press multiple moving targets when playing the piano, and (ii) exploring heuristics by experts marking various difficult parts of songs, and deciding on specific interventions needed for marked parts. Using models and input from the experts we will design and build an adaptive piano roll training system to better support piano learners. We will evaluate and compare these models in various user studies involving novices trying to play piano pieces and develop their improvisation skills. We intend to uncover whether these adaptive visualisations will be helpful in the overall training of piano learners. Additionally, these models and adaptive visualisations will allow us to discover affordances that can potentially improve piano learning in general.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**; visualisation.

KEYWORDS

extended reality, spatiotemporal moving target selection, heuristics, piano roll, visualisation, piano learning

ACM Reference Format:

Jordan Aiko Deja. 2021. Adaptive Visualisations Using Spatiotemporal and Heuristic Models to Support Piano Learning. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '21)*, June 21–25, 2021, Utrecht, Netherlands. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3450613.3459656>

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).
UMAP '21, June 21–25, 2021, Utrecht, Netherlands
© 2021 Copyright held by the owner/author(s).
ACM ISBN 978-1-4503-8366-0/21/06.
<https://doi.org/10.1145/3450613.3459656>

1 PROBLEM AND BACKGROUND

The process of learning a musical instrument such as the piano is usually tedious, repetitive and overwhelming. It requires keen hand-eye coordination, mastery of music sheet notation and more importantly, hours of continuous practice. All this can highly increase the cognitive load of learners. Having a tutor or a maestro usually provides an improved learning experience since novices can receive immediate feedback during their practice. However, tutors are usually expensive and are not always readily-available (e.g. when practicing alone). The learning process also varies depending on the type of a music instrument and its availability (portable vs. stationary) and costs. All of these are some of the known factors that make learning a music instrument a challenging task.

Several technology interventions have been introduced to assist in one or some of the challenges in learning music instruments ranging from supportive tutoring prototypes, ergonomics, groupware and others [6, 8]. Even cultural and societal factors have been considered along with technological interventions [4, 5]. More recently, Augmented Reality (AR), the approach of overlaying digital elements to the physical world, has been introduced as a tutor substitute for music instrument learners. The availability of AR SDKs lead to a rise of AR prototypes being developed and studied [28]. Most of the innovations introduced by these AR piano systems are either in hardware [2, 9], learning modes [27] or visualisations [3]. While reporting on improvements in the learning process of novices, no prototype (to the best of our knowledge) considered music temporality in the design of adaptive visualisations. Music has a temporal component described by rhythms and other factors. It has been observed that introducing irregularities in temporal component has a negative effect on the listening experience [22]. However, introducing small, systematic temporal irregularities in the music sheets have led to improvements in playing a piano [15]. While these improvements have been observed on the traditional piano, they have yet to be explored in the domain of AR piano prototypes. In the context of AR piano roll visualisations, users having to press the right key at the right time given a visual stimuli would then describe the spatiotemporal applicability of music.

Understanding how novices perform during the learning process plays an important role in this research. General studies on learning systems have explored cognitive load (and other factors) to potentially assist in developing expertise of learners. Yuksel et al. [33] introduced an adaptive learning interface that adjusted based on the current brain state (EEG signal) of the learner. He posits that having a dynamic and adaptive interface led to an increased accuracy and speed of learners while doing brain-based adaptive tasks.

Cognitive load has also been explored in music learning. The work of Klepsch et al. [13] measured the cognitive load of learners, and how the piano roll as a visual stimuli may potentially overwhelm the user, with inconclusive results. There are some works who have explored understanding cognitive load, user personalities and its effect to the users spatial memory [14]. Despite the extensive body of research on using technology in learning, none of the studies have integrated the temporal component of music, tried to predict errors and adapt piano roll visualisations accordingly.

In this work, we will focus on creating models for predicting user errors and adapting piano roll visualisation based on these models. More specifically, we are going to investigate whether these interventions affect learning. We chose two approaches to build the models described. The first one will be based on the spatiotemporal modelling work by Kim et al. [12], Lee et al. [17], Lee and Oulasvirta [19], Liao et al. [21] where they have modelled and predicted error rates of users doing spatiotemporal tasks such as batting a virtual baseball, clicking a moving and tricky target, and pressing a tactile button at the right time. It also considers three factors namely (i) the user's internal time keeping mechanism, (ii) Fitt's Law and (iii) the effects of visualisations in Cognitive Load Theory (CLT) [11, 13]. In focus, users possess an internal time-keeping mechanism when given an external stimulus following the Wing-Kristofferson (WK) model (the synchronization and its performance given a sequence of external events such as the metronome [31, 32]. This enables a linear phase-error correction mechanism among users [25, 29]) allowing them to reduce errors in in pointing activities such as pressing. Also, Fitts' Index of Difficulty (ID - in Fitts' Law, the component that quantifies task difficulty through the quotient of target width and distance [7, 10]) explains and supports how the quality of pointing on a single moving target [23, 24] maybe improved as well. Existing previous work on spatiotemporal models have been done for single-target moving objects and have not explored multi-targetted scenarios such as piano key-pressing. The second approach will be based on the heuristics by experts marking various difficult parts of songs, and deciding on specific interventions needed for marked parts. Later, the models will adapt according to each individual player and their performance. For both approaches we will build an AR projection based piano roll system that will allow us to collect the spatiotemporal data of its users. These data will be used to build spatiotemporal and/or heuristic models that will help us design adaptive visualisations.

We believe that systems can support piano learning by designing visualisations as an intervention to assist learners of varying skill levels. We propose *PIANO 2.0* inspired and built on top of the work by Rogers et al. [27]. From a prototype that we will initially build with static visualisations, we will incrementally introduce adaptive visualisations that take into account the models described. Participants will be invited to train with our piano roll prototype where we shall observe its effects to the piano learning experiences.

2 RELATED WORK

2.1 Spatiotemporal pointing and moving target selection

Spatiotemporal moving target selection has been so far mostly investigated outside augmented reality (AR) by modeling, analysing

and predicting user error rates. Exploring spatiotemporal pointing in AR is relatively new. The works of Arora et al. [1], Lee et al. [20], Liao et al. [21] have laid the groundwork on modeling and measuring spatiotemporal pointing. First by investigating temporal pointing and predicting errors in a task consisting of pressing a button. Recently they explored modelling in XR environments by batting a virtual baseball and authoring animations using gestures in an AR space.

Lee and Oulasvirta [19] and Lee et al. [18] built models to predict players' performance and error rates for some real-time games that are played with a single button — temporal pointing. Their models could successfully predict players' performance while playing popular games such as Flappy Bird and Cake Tower. The presented models can be applied to adaptively change the game's difficulty level by changing latency or speed of moving objects. The study of Lee et al. [17], investigated collision events of a hand with a virtual object by throwing, pushing or pulling it. In their prototype called Boxer, users received a salient sensory feedback on their palm when a pointer (palm) made a contact with a moving virtual object (a virtual ball). The feedback was triggered when the pointer reached a minimum speed after the collision. The researchers compared this spatiotemporal pointing with temporal pointing task (just pressing a button at the right time) presented in the study described before. Based on their findings, spatial precision in collisions improved by 26.7%. Their study also reported that there were no observed differences in temporal precision.

The work of Kim et al. [12] presented an activation technique called impact activation (IA) that describes the point where a button is activated at its maximal impact point. Based on their findings, IA as a technique is most useful during particularly-rapid repetitive button pressing activities, which are usually observed in games and music applications. While their study focused more on rapid button pressing, their findings were able to report on user's timing accuracy and how it improved significantly by using IA. The proposed technique can be implemented in modern push-button setups that generate a continuous signal. In music teaching systems, pressing the piano key resembles an action of pressing a button. Users pressing on a setup like a piano teaching system may potentially take advantage from accuracy improvements that use impact activation.

The work of Park and Lee [24] designed an Intermittent Click Planning (ICP) model on moving targets. The study aimed to understand and model *submovements* and the planning process that users usually undertake before clicking a moving target. This ICP model predicted error rates between gamers and non-gamers when trying to click on moving tricky targets. Based on their findings, gamers and more experienced users performed better (with reduced errors) than their non-gamer counterparts. While this study focused on clicking a moving target, the model and the internal time-keeping mechanism behind the click planning can be used to understand spatiotemporal interactions of piano novices in AR systems as well.

Exploration on modeling spatiotemporal pointing for multiple targets such as music learning, and its effects on the learning process is, to the best of our knowledge, nonexistent. As such, we intend to fill this gap by attempting to model multi target spatio temporal moving target selection (*RQ1*). Our aim is to expand the presented work by building models and apply them in the context of learning music such as piano learning (*RQ2*).

2.2 Piano teaching systems, augmented reality and visualisations

Most of the recent contributions in AR music teaching systems focus on either (1) introducing novel interfaces [2, 9], (2) different learner modes for the users [27, 30], or (3) improving graphical rendering of the visualisations [3, 34] (RQ0).

The work of Barakonyi and Schmalstieg [2] presented an AR piano tutor. The prototype used a webcam, a monitor and a MIDI keyboard. The webcam captured the keyboard that was shown on the monitor together with digital information instructing users to hit certain keys in a defined order as well as giving audio feedback as to which keys have been pressed correctly and which were pressed by mistake. The system also included an advanced music composition tool by analysing the tunes currently being played and suggesting background chords and appropriate solo melodies. This technology allowed it to understand its users but did not consider other factors such as cognitive load and spatiotemporal pointing data. The prototype of Huang et al. [9] presented a markerless AR based piano teaching system. It used virtual hands overlaid on the real keyboard, which allowed the beginners to practice playing the piano by following the overlaid hands.

As in previous examples, the visualisations used in this prototype did not consider spatiotemporal pointing data. The paper by Chow et al. [3] presents an AR prototype using a head mounted display. The prototype is targeting people who practice the instrument on their own (how it is done traditionally) and lack feedback on how to improve their playing as well as motivation for learning. Their prototype addressed these two shortcomings by visualising “falling” notes, providing direct feedback, and including game elements to learning. The findings show that beginners improved their notation literacy. While the visualisations were effective, we believe that this can be improved further by considering pre-built user models.

The work of Weing et al. [30] presents a prototype that enhances musical instrument learning with projected visualisations. Their P.I.A.N.O. prototype aims to support learning to play a piano by considering the learning curve of beginners and addressing hard-to-learn music notations. These notations are augmented with an alternative representation and both are projected onto the piano. Aside from the design of a piano prototype with interactive visualisations and projections, their study also proposed three different learning modes that support novice learners (listen, practice, play modes). They were able to improve on top of the work of Chow et al. [3] by using gamification and interactivity to prolong students’ motivation. The P.I.A.N.O. was improved further in [27] by mapping the correct visualisations with extra articulation or enhanced piano roll notation as referred to by authors. Their findings measured (i) a significantly lower cognitive load, (ii) an improved user experience, and (iii) an increase in perceived music quality rated by the experts as compared against non-projected piano roll notation.

None of these studies took users’ response times into account, and none of them were based on the pre-built spatiotemporal pointing or other models in order to better support piano learning processes based on their performance. Our research will fill this gap by designing spatiotemporal-aware visualisations (RQ1, RQ2) based on the pre-built models that take user data into account, which will, in our opinion improve piano learning. We shall also use these

models to help piano learners improve their improvisation skill which has not been done in any existing literature (at the best of our knowledge) (RQ3).

3 RESEARCH QUESTIONS AND RESEARCH PLAN

3.1 Research Questions and Hypotheses

The focus of this research will be on exploring augmented piano systems anchored on the general research question: “How can we support piano learners using adaptive visualisations based on spatiotemporal and/or heuristic models”? The models will not only allow us to adapt visualisations to individual learners but also to understand the differences between the way they use the piano. We divide this general research problem into more specific research questions:

RQ0: What other technological interventions have been introduced to support piano learning? We believe that AR has been an effective piano learning supporting technology. However, in order to proceed with the succeeding RQ’s we also need to survey and review the landscape of technology that supports piano learning as well as interview piano teachers and teachers of piano didactics. By doing this, we can draw more inspirations towards better designing adaptive visualisations beyond the scope of AR and position our contribution based on the existing landscape of technology.

RQ1: How to build multi-target pointing models to predict user errors while using the piano roll? We predict that based on the success of earlier studies on single-target spatiotemporal pointing and moving target selection in AR [17, 19, 24], models of learners usage can also be used to build adaptive visualisations that support piano learning. Similarly, heuristics based models should also be possible to build for such multi-target pointing.

RQ2: How to improve the learner performance, user experience and sound quality of novices when learning the piano using adaptive visualisations designed from spatiotemporal and/or heuristic models? We believe that if we consider spatiotemporal data of learners or heuristics, we can design adaptive visualisations that will serve as intervention to better support their learning [26]. Lee [16] states that determining the appropriate level of difficulty in game design is essential to ensure player experiences in an environment. By predicting error rates from player’s activities, we could better support learning experiences in general. We believe that the same should be true in a similar learning scenarios such as playing musical instruments. We will evaluate this in terms of improved student performance (measure accuracy), better user experience (usability tests and Attrakdiff), and sound quality (with the help of expert rating). Novices progress differently if they use adaptive visualisations in an AR piano prototype that guide them compared to using non adaptive static visualisations. We will explore the effects of these visualisations in the learning process of piano novices.

RQ3: How do novices learn improvisation using adaptive visualisations designed from spatiotemporal and/or heuristic models? Based on the results of our expert interviews, improvisation is the least-focused on but equally-important skill for piano learners. Similar to RQ2, we believe that adaptive visualisations can

Table 1: Table of Conditions: User Studies

Viz / Piano roll type	Classic piano roll	Improv piano roll
No viz	Model & Assess phases	Model & Assess phases
Static viz	Model & Assess phases	Model & Assess phases
Spatiotemporal viz	Assess phase	Assess phase
Heuristic viz	Assess phase	Assess phase

aid as a learning supplement/intervention in encouraging piano learners to improvise during their performances.

3.2 Method

This research will have five (5) distinct phases. These are (1) Explore, (2) Model, (3) Develop, (4) Assess, and (5) Expand. These phases have been mapped with the RQ's above, and are described below:

In **Explore–Survey of Piano Learning Support Technologies**, we already reviewed existing prototypes and modalities that support teaching and learning piano. This phase also included expert interviews (piano teachers and teachers of piano didactics), literature review and prototype design. A systematic literature review was done on a set of augmented piano prototypes introduced within the last 15 years. The findings of this phase revealed that there are two gaps in the field: the lack of adaptive technologies for piano learning and the lack of support for developing improvisation skills. The combined insights of HCI and UX practitioners who *know how to design systems*, and insights from interviews of piano users who *know how to use and teach the piano* will help us to design the prototype in the next phase.

In **Develop–Introducing PIANO 2.0: An Augmented Piano Projection System**, we decided to build upon the **P.I.A.N.O.** prototype by [27, 30], which will be a scalable version of the former to accommodate dynamic adaptive classical visualisations and improvisation visualisations. This prototype will initially be developed with static piano roll visualisations that will be projected on top. It will be equipped with sensors and modules that enable spatiotemporal data collection and/or heuristic-based rules and features. It will also have an *Improvise* module which allows students to learn the piano beyond the already-available *Practice*, *Listen* and *Play modes* from the current version of the prototype. An open-source documentation of the project will also be shared.

In **Model–Understanding Novice Motion using Spatiotemporal Pointing**, we will investigate whether it is possible to build spatiotemporal models from users' movements, key presses and patterns while using PIANO 2.0 by adapting the existing one-target spatiotemporal models. This will be done by collecting their usage data and building an initial model which will then be updated on continuous use. This will allow us to analyse and predict users' error rates, which we will then use to build and optimise adaptive visualisations. We will explore different configurations of the model such as one model per finger, one model per hand or one model for two hands. Additional models will be based on the heuristics from the experts marking various difficult parts of songs, and deciding on specific interventions needed for marked parts. These models will be trained and validated hand on hand during this phase. When we achieve desirable parameters, these will be used to augment the visualisation engine that novices can use and test with.

In **Assess–Evaluating how novices learn in AR piano under different learning conditions** phase, we will explore how adaptive visualisations contribute to novice learning experiences. We will invite novice participants to learn using our PIANO 2.0 prototype specially-equipped with spatiotemporal sensors following a between-subject study design. Participants from a local secondary school aged 12 and up will be invited to train using our prototype using classical piano roll visualisations following our specified training programme. The participants will be exploring three conditions: (i) no visualisation, (ii) non adaptive visualisation, and (iii) adaptive visualisation. Participants will be using PIANO 2.0 for multiple, succeeding sessions. We will measure if there is an improvement in terms of user experience and piano playing. If possible, the recordings and outputs of the participants will also be assessed in a separate study with the help of experts who will give their rating on their musical output. We will also explore the development of improvisation skills of learners using the similar test protocol. During the first phase, the majority of interviewees revealed that the current piano teaching approaches in music schools do not put enough emphasis on the improvisation. Our modified piano roll for improvisation will be, to our knowledge, the first visualisation of its kind. As with the regular piano roll, we will also explore how the adaptation effects the learning of the student. Details on the conditions and parameters of these user studies are described in Table 1.

3.3 Contributions

The work presented will provide the following contributions to the field:

- (1) a survey of prototypes exploring the existing landscape of augmented piano technologies and piano roll visualisations;
- (2) multi-target spatiotemporal pointing models to predict user errors while using the piano roll;
- (3) adaptive visualisations method for piano roll based on spatiotemporal and/or heuristic models;
- (4) modification of the existing piano roll designed to develop users' improvisation skills;
- (5) several user studies involving: (i) expert interviews eliciting current gaps and design recommendations; (ii) a study exploring how different adaptive visualisations will affect users learning if compared to the baseline (static piano roll); (iii) a study exploring novel piano role visualisation for developing improvisation skills;
- (6) design guidelines/rules for implementing adaptive visualisations in piano learning.

4 WORK TO DATE AND FUTURE WORK

4.1 Initial Study - Explore phase

As of time of writing, we are at the end of the **Explore** phase of the research presented. A survey paper on 61 augmented piano prototypes is being prepared for submission. We highlight the extensive contribution of prototypes with respect to specific themes in piano learning as well as the gaps such as the lack of adapting the technology interventions to individual users in order to better support their learning needs. The second part of this is based in expert interviews with piano teachers and teachers of piano didactics

(currently $n = 4$, 22 average years of experience). In these interviews we are discussing the teaching process, design ideas and validating assumptions with regards to the design of the prototype and the results of the survey. Their insights will be considered in the design of the piano prototype and the design of experiments.

4.2 Prototype - Develop phase

A modified MIDI keyboard is currently being prepared and equipped with special sensors that should be able to capture spatiotemporal movement of its users. This prototype is also being bundled with an AR projection module that will help in the data collection phase of this study.

4.3 Future work

Currently we are in the middle of phase 2 as described in our Method section. This will be followed by the Model and Assess phases respectively.

REFERENCES

- [1] Rahul Arora, Rubaiat Habib Kazi, Danny M Kaufman, Wilnot Li, and Karan Singh. 2019. MagicalHands: Mid-Air Hand Gestures for Animating in VR. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology*. 463–477.
- [2] István Barakonyi and Dieter Schmalstieg. 2005. Augmented reality agents in the development pipeline of computer entertainment. In *International Conference on Entertainment Computing*. Springer, 345–356.
- [3] Jonathan Chow, Haoyang Feng, Robert Amor, and Burkhard C Wünsche. 2013. Music education using augmented reality with a head mounted display. In *Proceedings of the Fourteenth Australasian User Interface Conference-Volume 139*. 73–79.
- [4] Peter Cope and Hugh Smith. 1997. Cultural context in musical instrument learning. *British Journal of Music Education* 14, 3 (1997), 283–289.
- [5] Andrea Creech. 2010. Learning a musical instrument: The case for parental support. *Music Education Research* 12, 1 (2010), 13–32.
- [6] Ryan Daniel. 2006. Exploring music instrument teaching and learning environments: Video analysis as a means of elucidating process and learning outcomes. *Music Education Research* 8, 2 (2006), 191–215.
- [7] Paul M Fitts. 1954. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology* 47, 6 (1954), 381.
- [8] Dominique Fober, Stéphane Letz, and Yann Orlarey. 2007. Vemus-feedback and groupware technologies for music instrument learning.
- [9] Feng Huang, Yu Zhou, Yao Yu, Ziqiang Wang, and Sidan Du. 2011. Piano ar: A markerless augmented reality based piano teaching system. In *2011 Third International Conference on Intelligent Human-Machine Systems and Cybernetics*, Vol. 2. IEEE, 47–52.
- [10] Raoul Huys, Hester Knol, Rita Sleimen-Malkoun, Jean-Jacques Temprado, and Viktor K Jirsa. 2015. Does changing Fitts' index of difficulty evoke transitions in movement dynamics? *EPJ Nonlinear Biomedical Physics* 3, 1 (2015), 8.
- [11] Mohammed K Khalil, Fred Paas, Tristan E Johnson, and Andrew F Payer. 2005. Design of interactive and dynamic anatomical visualizations: the implication of cognitive load theory. *The Anatomical Record Part B: The New Anatomist: An Official Publication of the American Association of Anatomists* 286, 1 (2005), 15–20.
- [12] Sunjun Kim, Byungjoo Lee, and Antti Oulasvirta. 2018. Impact activation improves rapid button pressing. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–8.
- [13] Melina Klepsch, Florian Schmitz, and Tina Seufert. 2017. Development and validation of two instruments measuring intrinsic, extraneous, and germane cognitive load. *Frontiers in psychology* 8 (2017), 1997.
- [14] Sébastien Lallé and Cristina Conati. 2019. The role of user differences in customization: a case study in personalization for infovis-based content. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*. 329–339.
- [15] Edward W Large and Caroline Palmer. 2002. Perceiving temporal regularity in music. *Cognitive science* 26, 1 (2002), 1–37.
- [16] Byungjoo Lee. 2016. *Temporal Pointing*. <http://www.leebyungjoo.com/Temporal-Pointing-1>
- [17] Byungjoo Lee, Qiao Deng, Eve Hoggan, and Antti Oulasvirta. 2017. Boxer: a multimodal collision technique for virtual objects. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction*. 252–260.
- [18] Byungjoo Lee, Sunjun Kim, Antti Oulasvirta, Jong-In Lee, and Eunji Park. 2018. Moving target selection: A cue integration model. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–12.
- [19] Byungjoo Lee and Antti Oulasvirta. 2016. Modelling error rates in temporal pointing. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 1857–1868.
- [20] Injung Lee, Sunjun Kim, and Byungjoo Lee. 2019. Geometrically compensating effect of end-to-end latency in moving-target selection games. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.
- [21] Yi-Chi Liao, Sunjun Kim, Byungjoo Lee, and Antti Oulasvirta. 2020. Button Simulation and Design via FDVV Models. *arXiv preprint arXiv:2001.04352* (2020).
- [22] Edward A Lippman. 1984. Progressive temporality in music. *Journal of Musicology* 3, 2 (1984), 121–141.
- [23] I Scott MacKenzie and William Buxton. 1992. Extending Fitts' law to two-dimensional tasks. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 219–226.
- [24] Eunji Park and Byungjoo Lee. 2020. An Intermittent Click Planning Model. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [25] Jeff Pressing. 1998. Error correction processes in temporal pattern production. *Journal of Mathematical Psychology* 42, 1 (1998), 63–101.
- [26] Remy MJP Rikers, Pascal WM Van Gerven, and Henk G Schmidt. 2004. Cognitive load theory as a tool for expertise development. *Instructional Science* 32, 1-2 (2004), 173–182.
- [27] Katja Rogers, Amrei Röhlig, Matthias Weing, Jan Gugenheimer, Bastian Könings, Melina Klepsch, Florian Schaub, Enrico Rukzio, Tina Seufert, and Michael Weber. 2014. Piano: Faster piano learning with interactive projection. In *Proceedings of the Ninth ACM International Conference on Interactive Tabletops and Surfaces*. 149–158.
- [28] Marc Ericson C Santos, Angie Chen, Takafumi Taketomi, Goshiro Yamamoto, Jun Miyazaki, and Hirokazu Kato. 2013. Augmented reality learning experiences: Survey of prototype design and evaluation. *IEEE Transactions on learning technologies* 7, 1 (2013), 38–56.
- [29] Dirk Vorberg and Hans-Henning Schulze. 2002. Linear phase-correction in synchronization: Predictions, parameter estimation, and simulations. *Journal of Mathematical Psychology* 46, 1 (2002), 56–87.
- [30] Matthias Weing, Amrei Röhlig, Katja Rogers, Jan Gugenheimer, Florian Schaub, Bastian Könings, Enrico Rukzio, and Michael Weber. 2013. PIANO: enhancing instrument learning via interactive projected augmentation. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*. 75–78.
- [31] Alan M Wing and AB Kristofferson. 1973. The timing of interresponse intervals. *Perception & Psychophysics* 13, 3 (1973), 455–460.
- [32] Alan M Wing and Alfred B Kristofferson. 1973. Response delays and the timing of discrete motor responses. *Perception & Psychophysics* 14, 1 (1973), 5–12.
- [33] Beste F Yuksel, Kurt B Oleson, Lane Harrison, Evan M Peck, Daniel Afergan, Remco Chang, and Robert JK Jacob. 2016. Learn piano with BACH: An adaptive learning interface that adjusts task difficulty based on brain state. In *Proceedings of the 2016 chi conference on human factors in computing systems*. 5372–5384.
- [34] Feng Zheng, Ryan Schubert, and Greg Weich. 2013. A general approach for closed-loop registration in AR. In *2013 IEEE Virtual Reality (VR)*. IEEE, 47–50.