

Learning to Play Piano in the Real World

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Abstract—Towards the grand challenge of achieving human-level manipulation in robots, playing piano is a compelling testbed that requires strategic, precise, and flowing movements. Over the years, several works demonstrated hand-designed controllers on real world piano playing, while other works evaluated robot learning approaches on simulated piano scenarios. In this paper, we develop the first piano playing robotic system that makes use of learning approaches while also being deployed on a real world dexterous robot. Specifically, we make use of Sim2Real to train a policy in simulation using reinforcement learning before deploying the learned policy on a real world dexterous robot. In our experiments, we thoroughly evaluate the interplay between domain randomization and the accuracy of the dynamics model used in simulation. Moreover, we evaluate the robot’s performance across multiple songs with varying complexity to study the generalization of our learned policy. By providing a proof-of-concept of learning to play piano in the real world, we want to encourage the community to adopt piano playing as a compelling benchmark towards human-level manipulation. We open-source our code and show additional videos at www.lasr.org/research/learning-to-play-piano.

I. INTRODUCTION

Playing the piano requires humans to master contact-rich hand movements dictated by the timing and tone they intend to produce. This mastery is not learned quickly but through extensive practice, which requires humans to control their actions based on the haptic and auditory feedback received with each key pressed on the piano. In addition, human hands are an extraordinary research subject due to their unmatched dexterity, precision, and adaptability. These capabilities have evolved to perform various tasks, from delicate manipulations like sewing to powerful tasks like shot-put. This makes human-like hands a natural inspiration for robotic systems. In robotics, much attention has been paid to tasks such as in-hand object rotation, where the goal is to develop and optimize object manipulation through intricate movements [1, 15, 7, 8]. These studies often achieve efficient manipulation by exploiting unnatural and sometimes non-anthropomorphic motions to improve control and precision. Although such techniques yield impressive results, they often diverge from the natural movements of the human hand, which could limit their applicability to tasks that require more human-like actions. Playing a musical instrument like the piano is an exceptional example of human-like hand function.

Piano playing demands a high level of motor control, coordination, and precision, all while closely aligning with



Figure 1: In this work, we demonstrate a proof-of-concept for learning to play piano with a real world robot. To achieve this, we employed a multi-finger robot hand and a Sim2Real approach. Experimental results show that the robot can learn to play several simple pieces successfully, after training exclusively in simulation.

the natural movements of human hands. This makes it an ideal scenario for exploring Sim2Real transfer, where the objective is to train an agent in simulation capable of performing in the real world. By focusing on playing piano with a human-like hand, this research aims to bridge the gap between the abstract, often unnatural solutions of robotic manipulation and the fluid, natural motions required to mirror the human approaches to complex tasks more closely.

In this work, we train a reinforcement learning policy in simulation that is applicable in the real world. The agent’s task is to play simple songs, such as the children’s song ”Twinkle Twinkle Little Star”, with a multi-finger Allegro hand on a real world piano. We define the observation space of the model that comprises the notes that need to be played, the current joint positions of the hand, and the subsequent keys pressed at that time step. Our work is based on the open-source training environment Robopianist-Suite [18]. However, since our primary objective is to deploy the learned policy in the real world, we made numerous changes at the system level. Moreover, due to the changes in the environment, the reward function originally used in the roboopianist environment was no longer

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applicable. This pushed us to design a new reward function that is applicable to hands with an arbitrary number of fingers and does not depend on pre-known fingering data. Further, to bridge the Sim2Real gap, we utilized domain randomization of simulation parameters, such as joint dampening, friction coefficients, and spring stiffness. To apply the learned policy in the real world, we developed a system using ROS to control the robotics based on the actions of the agent.

II. RELATED WORK

Understanding the role of robotic systems in playing musical instruments goes a long way back to when highly sophisticated robots such as Takanishi’s Anthropomorphic Flutist Robot [12] that could mimic human respiratory systems were utilized to play the flute. Similarly, early works concerning robots playing the piano indicate the extensive effort made by researchers who built humanoid-like robots that leveraged precise finger-arm movement for rendering tunes [3]. Further works also explored the development of intelligent algorithms [6] and control systems [5] for anthropomorphic robots designed to play the piano. Although path paving, most of the works described heavily relied upon pre-programmed movements, limiting the robot’s ability to adjust to musical styles or improvise on existing scores. Therefore, we move away from traditional methods to a more learnable and robust methodology. Instead, we train the policy in the simulation to play a musical piece without any hard-coded or pre-programmed knowledge.

Moreover, playing the piano is a challenging benchmark for dexterity and the contributions in this field are very limited. The contribution of [11] focused on using inverse kinematics to play piano with Shadow hands in the real world, which does not utilize machine learning. In contrast, the contribution by Qian et al. [9], used imitation learning based on YouTube videos to play piano in a simulated environment. Research with robots and piano is novel, and initial works in simulation have demonstrated that learned agents can play simple songs and chords in a simulated environment [17, 18]. With the introduction of Robopianist [18], it was shown that by leveraging the reinforcement learning algorithms, an agent can be trained to play advanced music with two simulated Shadow hands. Furthermore, systematic reinforcement learning approaches in simulation elaborate on utilizing touch feedback from vision-based tactile sensors [4, 16], to teach a robot hand to play the piano [17]. Unlike most prior works, which focus on developing a paradigm to teach robot hands to play in simulation, we prioritize both teaching a robot hand to play the piano in simulation and translating this learned knowledge into a real world environment.

Sim2Real in robotics has seen widespread research, with a primary focus directed to inducing natural and stable finger gaits and human-like dexterity onto the robots [8]. In our work, we aim to replicate similar human-like learnability during the simulation phase, where we utilize domain randomization to help reinforce the knowledge of the robot and, at the

same time, provide scope for generalizing on different musical scores in the real world.

III. LEARNING TO PLAY PIANO IN THE REAL WORLD

Hardware Configuration. The hardware setup is shown in figure 2b. We use a UFACTORY xArm7 to move the end effector along a specified axis parallel to the piano. This mimics the movement of the human forearm.

Attached to the end effector is a left-sided Allegro hand v4.0. It consists of 4 fingers with 4 joints per finger, leading to 16 joints in total. The thumb joints are not used in this contribution because they can barely reach the piano, leading to 12 active joints. Further, each of the fingertips is replaced with a 3D-printed finger of approximately the dimensions of a human finger. This is necessary because the default fingertips of the Allegro hand are wider than a key, which makes it impossible to play only one note at a time.

As a piano, we use the M-Audio Keystation 49e MIDI Keyboard, which contains four octaves. Every keypress and every release triggers a MIDI event, which is forwarded to the host computer. This allows the agent to observe the currently pressed keys, however, the exact degree of the keypresses is unknown.

Simulation Environment. The environment is based on the *robopianist* environment [18], which was built using the Mujoco physics engine [13] with *dm_control* [14] as a wrapper for RL tasks. The scene of the simulation is displayed in Fig. 2a. It consists of the Allegro hand with 3D printed fingertips and a model of the M-Audio Keystation piano. The hand is modeled analogues to the real world with 12 active joints, 4 per finger. To move the hand parallel to the piano, we introduced another sliding joint for horizontal movement. The piano itself consists of 49 keys and 4 octaves. We still use the synthesizer of the *robopianist* environment, which is based on *fluidsynth*, but the sustain pedal was removed since it is not part of the real world environment.

Markov-Decision-Process. The task is modeled as a stochastic, partial observable MDP defined by the tuple (S, A, p, r, γ) .

- The state space S and the transition probabilities p are defined by the Mujoco physics engine. At each simulation step is the current state stored in the *environment.physics.data* object.
- The action space A consists of 13 continuous actions. One action per joint of the hand and one additional action for the wrist movement, parallel to the piano.
- The observation space O is 356 dimensional and is explained in more detail in the Table I. Note that the states of the keys are discrete. This makes playing the piano more demanding because the agent cannot hover with the fingers on the keys to observe the environment, as described in the *robopianist* [18]. Unfortunately, it is necessary because the MIDI standard used by the piano does not include partially pressed keys. Another contrast to the *robopianist* environment [18] is that the observation space does not include any fingering information. This is



(a) Simulated hand and piano.



(b) Real world hand and piano

Figure 2: Comparison of the simulated training environment to the real world. The real world environment consists of a multi-finger Wonik’s Allegro hand mounted on a Ufactory xArm7 robot arm and an M-Audio Keystation 49e MIDI keyboard. The fingertips of the Allegro hand are replaced with thinner 3D-printed fingertips that fit the dimensions of the piano to allow pressing a single key at a time.

Observations	Units	Dimension
Used joints of the Allegro Hand	rad	12
Slider for parallel movement	m	1
Currently pressed keys	one-hot-encoded	49
Currently targeted keys	one-hot-encoded	49
Targeted keys	one-hot-encoded	$5 * 49 = 245$
Total observation space	mixed	356

Table I: The observation space of the agent.

due to the Allegro hand having only 4 fingers, which makes regular “human” fingering not applicable. The missing fingering information also has a negative impact on the exploration. For those reasons, a carefully chosen reward function is even more crucial to succeed in the exploration.

Reward Design. The reward function consists of four parts

$$r_{\text{total}} = r_{\text{energy}} + r_{\text{hand_position}} + r_{\text{keypress}} + r_{\text{sliding}},$$

each rewards certain behavior of the agent. We will briefly discuss the purpose of each part in this section. However, a more detailed discussion is included in Appendix VI-A.

The r_{energy} reward penalizes fast movements that need a lot of force. Further, it avoids oscillations that don’t lead to higher rewards.

The reward $r_{\text{hand_position}}$ is designed to guide the hand toward targeted keys. This is achieved by reducing the average distance between the palm of the hand and the targeted keys.

The r_{keypress} reward is the most important part of r_{total} because it encourages the agent to press the correct keys. The reward is designed based on two design requirements:

- 1) Pressing no keys should be worse than pressing the wrong keys.
- 2) Pressing the correct keys should be better than pressing the wrong keys.

Those requirements lead the exploration of the model towards pressing the correct keys without being “afraid” of pressing the wrong keys.

The r_{sliding} reward is designed to penalize fast sideways movement of the hand while keys are pressed. This avoids the local optimum where one finger is pressed statically while the wrist slider “selects” the key. Further, the penalty is doubled if two adjacent keys are pressed, which is unavoidable while sliding sideways.

Evaluation Metrics. To quantify the success of the agent we apply the same metric as in the robopianist [18] contribution. At each timestep, the current states of all piano keys are compared to the target states, addressing two questions:

- How reliable is the model at not pressing the keys it should not press? (Precision)
- How reliable is the model at pressing the keys it should press? (Recall)

Both, the precision and recall score range from 0 to 1. A score of 1 indicates that the agent performed perfectly in all timesteps according in this metric. Both metrics are combined using the harmonic mean to calculate the F1 score

$$F_1 = \frac{2}{\text{recall}^{-1} + \text{precision}^{-1}}.$$

We use the F1 score as our primary score to quantify the success of the agent. We also support the empirical statement made in the robopianist [18] that the F1 score represents the qualitative performance of the agent. Further, the F1 score is a common heuristic accuracy score in the audio information retrieval literature [10].

Our Workflow. Our workflow is separated into two phases:

First, we start with training a policy exclusively in simulation. This policy can then be used to play piano in the real world with an execution mode. In the following sections, we will discuss both phases in more detail.

Model Training. The policy is trained using DroQ [2], a soft actor-critic algorithm. Each model is trained for $1e6$ episodes, which takes about 47 min on a laptop with a GeForce RTX 4070 GPU and an i9-13980HX CPU with 32 cores. To

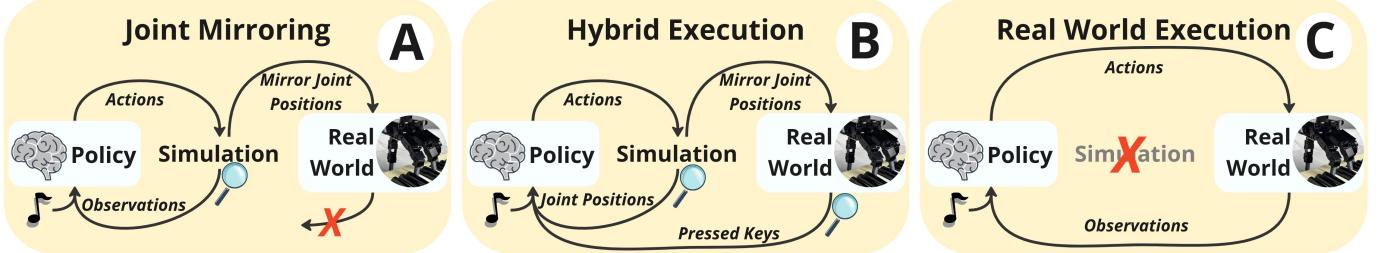


Figure 3: The diagram compares the three execution modes we introduced: A) In joint mirroring, the whole observation space is obtained from the simulated environment. B) In hybrid execution, only the pressed keys are based on the real world, while everything else is simulated. C) In real world execution, all observations are based on the real world.

reduce the Sim2Real gap, we utilized domain randomization of the following parameters:

- The height of the piano
- The starting position of the hand
- The dampening of the joints
- The stiffness of the joints
- The threshold of a key to be considered pressed
- The stiffness of the springs holding the keys
- The friction between the keys and the fingertips

Each simulation timestep is 0.005 s long. The current state is observed every 10th iteration, which leads to a control frequency of the policy of 20 Hz.

Execution Modes. To evaluate the trained policy in the real world, we introduce three modes of execution, which are also displayed in Fig. 3:

- 1) **Joint Mirroring:** In this mode are all observations based on the simulation. The real world robot mirrors the joint positions of the simulation into the real world. This leads to a deterministic sequence of actions, but it is impossible to adapt to the environment.
- 2) **Real World Execution:** This mode is the opposite of joint mirroring and the most intuitive approach. All observations are based on the real world and the actions are applied directly to the robot. No simulation is used in this mode.
- 3) **Hybrid Execution:** The observation space of the model is split into observations of the real world and observations of the simulation. This is possible because the simultaneous inference of the model and the simulation of the physics environment is possible in real time. For our purpose, the pressed keys are based on the real world, while the joint positions are based on the simulation.

Song Collection. In total, we validate our models on four different songs, each having a different characteristic:

- 1) **Twinkle Twinkle Little Star:** This song is a simple children's song. Its most relevant characteristic is the big interval at the beginning of the song and the natural flow of the song. It further serves as an everyday live example.
- 2) **C-Major-Scale:** Having a scale in the reportorial is useful since it evaluates how the model changes from one key to another. For humans, it is intuitive to use all the fingers

for playing the scale. We will discuss in the experiments whether our agent exploits the same strategy.

- 3) **D-Major-Scale:** The major difference between the C-Major scale and the D-Major scale is that the D-Major scale contains black keys as well. This allows us to observe the fingering technique of the agent while pressing black keys.
- 4) **Chord Progression:** In the first three songs, the agent only needs to press one key at a time. In this song we train on a series of four chords instead, which lets us evaluate the multi finger performance.

IV. EXPERIMENTAL RESULTS

We provide videos showcasing real world runs for each of the experiments on our website: www.lasr.org/research/learning-to-play-piano.

In this section, we experimentally answer the following questions:

A. How does our model perform? (Fig. 4)

Setup. To evaluate the performance of our approach, we trained four different songs. Each of those songs was trained twice on independent seeds, which led to eight models in total. Since every run in the real world differs, we executed each model three times. The figure shows the average and standard deviation of the precision, recall and the resulting F1 score for each song after using hybrid execution as introduced in Section 3. Other execution modes are evaluated in Section IV-B. As a reference for the Sim2Real gap is also the performance in simulation provided.

Results. All four songs have in common that the precision is higher than the recall score. A possible explanation is that optimizing the recall score is easier than optimizing the precision. When the robot hand presses a wrong key, then the agent will try to correct it. For the precision short, it is already sufficient to lift the finger since no wrong keys are pressed anymore. However, to improve the recall score, the agent needs to lift the finger, move it sideways, and press the correct key. This sequence of actions is significantly more demanding and takes more time. By the time this takes, a new key might be already targeted, resulting in skipping some keys.

Another explanation for the higher recall compared to the precision score is that maximizing the recall score is

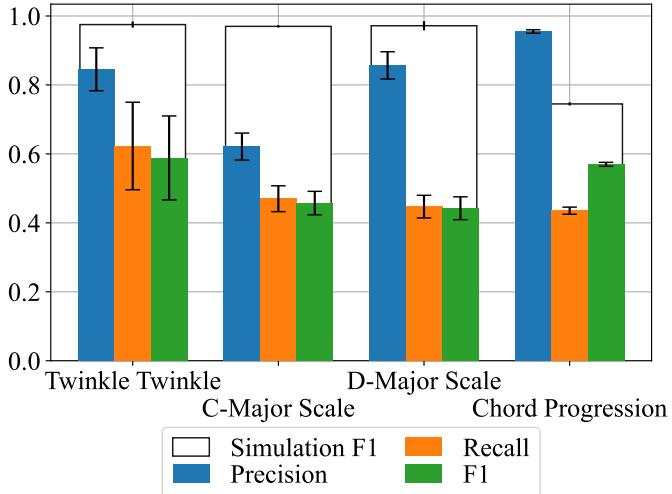


Figure 4: This diagram compares the performances of multiple songs in the real world with hybrid execution. For each song, we compare the precision, recall, and F1 score. As a reference is the F1 score, which was reached in the simulation, provided. The displayed data shows that although we observe a significant Sim2Real gap, we are able to play all four songs successfully. This indicates that our approach is generalizable and can be applied to other applications as well.

easier than maximizing the precision score. To maximize the precision, the agent needs to press at least all correct keys. But to maximize the recall, the agent can easily press no keys at all. This makes the precision, compared to pressing no keys at all, more demanding.

Another observation is that the Chord Progression performed the worst in the simulation, with an F1 score of ≈ 0.2 less than all other songs. This might be because playing chords requires the robot to press multiple keys at once. Therefore, the robot needs to organize multiple fingers at the same time, which might require a bigger model than just using one finger with occasional finger switches.

However, the observed F1 score in the real world is significantly above the average, with almost no variation. This results in the smallest Sim2Real gap of this experiment. A possible reason is that each chord needs to be pressed for a longer duration than a single key in the other songs. This enables the robot to correct itself more easily, decreasing the Sim2Real gap.

Conclusion. Our models are able to play all four songs successfully. Although they have a significant Sim2Real gap, the experiment shows that our approach is generalizable to multiple songs. This demonstrates the high potential of hybrid execution for other contributions.

B. Which execution mode has the most potential? (Fig. 5)

Setup. This experiment is an ablation study over our execution modes: joint mirroring, hybrid execution, and real world execution, which were introduced in Section III. No domain randomization was used for the joint mirroring and hybrid

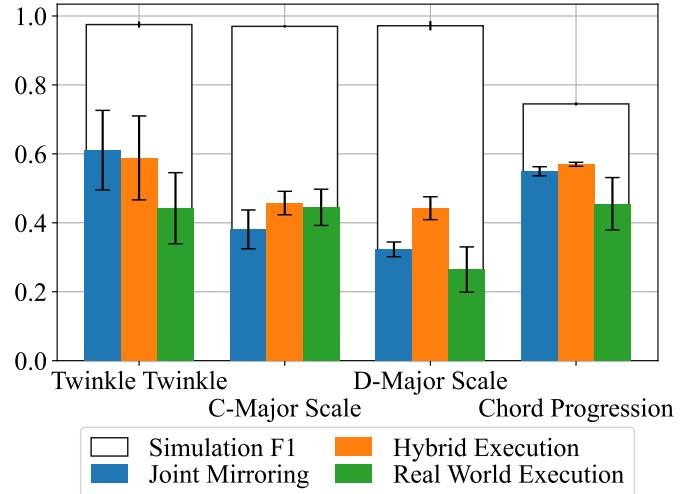


Figure 5: The diagram compares our execution modes on multiple songs. The best performing mode is hybrid execution. It allows the agent to correct itself while the joints behave similarly to what the agent was trained on in simulation.

execution. For the real world execution we decided to use a moderate intensity of domain randomization with $C_{dr} = 0.5$. The effect of domain randomization is further discussed in Section IV-C. Analog to the prior experiment, we trained each model configuration twice and executed each model 3 times per execution mode. Therefore, the figure shows the average and standard deviation of 6 runs for each mode.

Results. The diagram shows that the agent’s performance differs across the execution modes depending on the song. While joint mirroring performed among the best for Twinkle Twinkle Little Star and the Chord Progression, it performed worse than other modes for both scales. The real world execution, on the other side, performed well for the C-Major Scale but underperformed for all other songs. The hybrid execution was the best-performing mode for three out of four songs. The only exception is Twinkle Twinkle Little Star, where the hybrid execution mode was slightly behind joint mirroring. To understand the superiority of hybrid execution, we need to discuss the advantages and disadvantages of each execution mode separately.

When using joint mirroring, we don’t observe the real world, which makes it impossible to correct wrong keypresses. The advantage of this mode is that it does not need domain randomization, which reduces the resource requirements and the number of hyperparameters. The lack of adaptability is especially a problem for both scales since the model learned to slide sideways across the keys during the training. Unfortunately, this strategy is hard to execute in the real world since the finger slips differently every time. Since the agent does not observe the real world, it is also not able to correct those wrong movements.

The real world execution has the advantage of observing the whole state of the real world robot. This could allow the robot to react in the best way since no information is hidden.

Unfortunately, the additional information also requires a more robust model, which can be reached by utilizing domain randomization as shown in Section IV-C. However, domain randomization makes the training environment significantly more demanding. In our experiments, the model was not able to outperform the other execution modes.

The hybrid execution tries to combine both advantages. Most of the observations are still generated in simulation, which makes it easier for the agent to apply the learned strategies. However, by providing observations of the actually pressed keys, the robot is able to correct its behavior. This way, the agent behaves similarly to joint mirroring when the pressed keys match the currently pressed keys in the simulation. However, as soon as the simulation differs from the real world, the agent is able to correct itself. This is possible while not using any domain randomization at all, which makes the process even more favorable.

Conclusion. We showed that hybrid execution is the most promising execution mode for playing piano. It allows the agent to correct itself while being able to use the joints in the same way as they behaved during training. This makes hybrid execution modes especially interesting for future work with the goal of achieving human-like proficiency.

C. How does the intensity of domain randomization affect the real world performance? (Fig. 6, Fig. 7)

Setup. During this experiment, we trained 11 different configurations with an increasing intensity of domain randomization. To quantify the intensity of domain randomization, we introduce the parameter $C_{dr} \in [0, 1]$, with $C_{dr} = 0$ representing no domain randomization and $C_{dr} = 1$ representing the maximum amount of domain randomization. The models are then evaluated using real world execution. The figure shows the average and standard deviation of multiple runs. To reduce the tear on the robot and since the most interesting runs are the best performing runs, we decided to reduce the number of runs for higher and lower intensities of domain randomization. We calculate the average of at least 3 runs for each configuration. Further, for $C_{dr} \in [0.2, 0.8]$ we evaluated at least 5 runs and for $C_{dr} \in [0.3, 0.7]$ we evaluated 7 runs. The models are distributed across 4 different seeds.

Results. As visualized in Fig. 6, the performance in simulation decreases the more domain randomization is applied during training. This is because the environment behaves differently for every iteration when domain randomization is used, which requires a more robust model. When the number of iterations during the training stays the same, but the environment gets more demanding, a performance decrease is to be expected.

Further, we observe that the recall in simulation is higher than the precision. A possible explanation therefore is that our physics framework is based on soft body physics. This causes a tendency to press multiple keys at once, while only one key is intended to be pressed. This behavior ultimately reduces the precision while maintaining a high recall score.

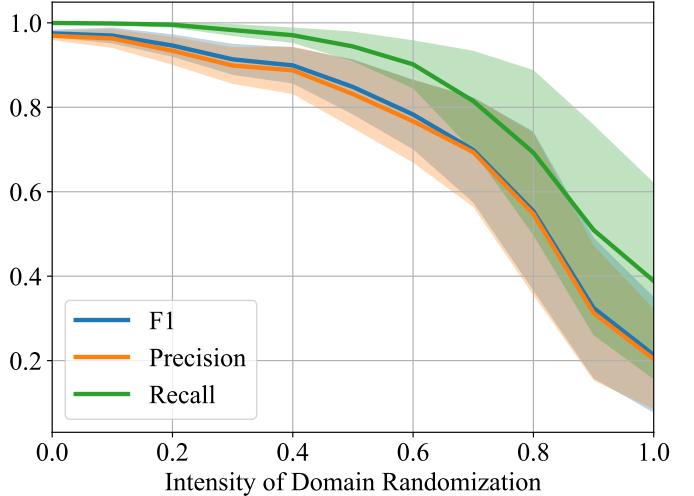


Figure 6: The diagram shows the effect of domain randomization on the performance in simulation. The more domain randomization is used, the more demanding the environment is. Since the number of training iterations is constant, this leads to a drop in performance.

The real world performance, on the other side, is displayed in Fig. 7. In contrast to the observations in simulation is the recall significantly lower than the precision score in the real world. This is because in the real world it is hard to press multiple keys with one finger. The plastic surfaces of the keys and fingers are slippery on each other, which causes the finger to slide onto one key. Once a key is pressed, the robot needs to lift the finger to press another key because the body of the adjacent keys acts as a border. This makes it harder to press the targeted key, since the agent might slide to the wrong side, reducing the recall score significantly.

The progression of the precision in the real world (Fig. 7) is similar to the progression of the precision in the simulation (Fig. 6). However, the real world precision is decreased by ≈ 0.2 for all intensities.

The recall on the other side has a very different progression. Without domain randomization, the recall is at ≈ 0.44 . Increasing the intensity of domain randomization leads to a reduced recall score of ≈ 0.35 at $C_{dr} = 0.2$. From there, the recall increases significantly until the maximum of ≈ 0.6 is reached at $C_{dr} = 0.6$, which also leads to the highest F1 score of ≈ 0.52 . For $C_{dr} > 0.6$ the recall drops rapidly.

A possible explanation for the similar progression of the precision is that an unintentionally pressed key can be corrected by just lifting the finger. This skill is simple to learn even without applying domain randomization. The recall on the other side, significantly benefits from the domain randomization. To correct from a mistake, the agent needs to move the finger to a different key. This requires more precise controls compared to just moving the finger up, which can be achieved by making the model more robust with domain randomization.

However, the decreased recall performance at $C_{dr} = 0.2$ is harder to explain. Our understanding is, that the agent seldom

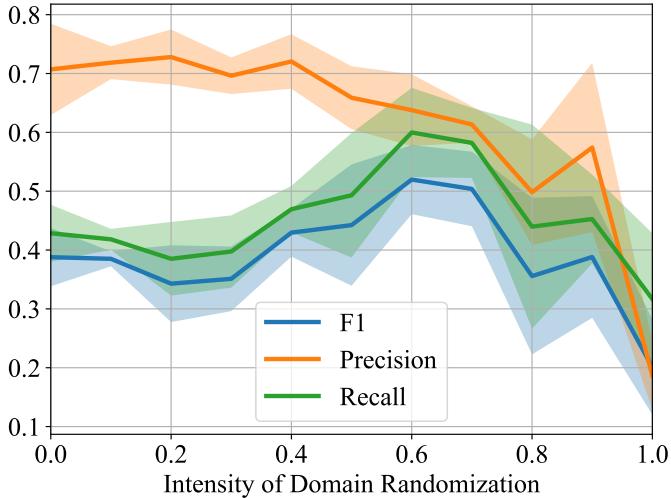


Figure 7: This diagram shows the effect of domain randomization on the model performance in the real world using real world execution. The precision has a progression similar as in Fig. 6, which indicates a constant Sim2Real gap. However, the recall improves significantly until a maximum at 0.6 where it starts dropping again. This is because the model gets more robust when more domain randomization is applied. Unfortunately, with too much domain randomization is the model not able to play piano successfully - neither in simulation nor in the real world.

ends up in those wrong states without domain randomization. Therefore, the agent is also not able to learn how to recover from those states.

For $C_{dr} > 0.6$ is a drop in performance expected since the performance in simulation drops as well.

Conclusion. The best performance can be achieved with moderate domain randomization. Too little domain randomization leads to worse performance since the model is not able to recover successfully after the environment behaved in a different way compared to the training. Too much domain randomization also worsens the performance since the model is not able to learn successfully during training. As a consequence of these results, we recommend researchers to carefully tune the intensity of domain randomization, since it significantly impacts the real world performance.

V. LIMITATIONS AND FUTURE WORK

In this work, we share our findings on how to teach a robot to play simple songs on a real piano. We demonstrated a proof of concept that utilized Sim2Real and a hybrid execution mode to play piano in the real world. However, our system possesses several limitations that could become the target of future research:

Song Generalization. Similarly to the robopianist [19], we observed that the performance decreases heavily when we attempted to test it on a different song than the one it was trained on. This means that we need to retrain the policy in simulation for each new song that we want to play. This is

undesirable, as we would instead prefer to train a single policy that at execution time is conditioned on a set of tablatures. However, preliminary results show that naively training on multiple songs does not seem to solve this issue. Future research should investigate how to achieve this contextual policy in a way that is robust and efficient.

Tactile Sensors. Another limitation of our work is the lack of additional sensing modalities, including touch sensing. In prior works [17], it has been shown that touch can enable the robot to perceive additional information about the environment and improve performance. We considered integrating existing touch sensing solutions, such as DIGIT [4]. However, these sensors are larger than a human finger, and resulted in pressing two keys at once. We believe that integrating future generations of tactile sensors that are smaller and omnidirectional would be valuable and an interesting research topic.

Dexterous Hands. Existing multi-finger robotic hands are still not as dexterous as a human hand. This is particularly evident in the limitations of finger abduction and flexion. Moreover, the use of the wrist seems to be rather important in humans. These hardware limitations resulted in the excessive movement of the whole hand at the level of the arm. It would be interesting to study in the future how to reduce these movements to obtain more natural movement and exploit future generations of more dexterous hands.

Fingers friction. The current 3D-printed fingertip used in our experiments is made from PLA which is very stiff. This reduces the contact area of the fingers, which reduces the friction, which leads to sliding on the keys while playing a song. This makes playing piano more demanding since the agent needs to balance the forces more precisely. Therefore, using fingertips made of softer materials, like TPU, silicone, or rubber, might increase the performance.

Bimanual playing. More complex piano songs require the use of two hands coordinating and playing at the same time. Our hardware setup is currently limited to a single hand, and this resulted in the use of relatively simple songs in our experimental setting. In the future, we hope to extend to the bimanual case and investigate how to learn more complex piano movements – thus being able to increase the overall difficulty of the played songs.

VI. CONCLUSION

In this work, we showcase the first proof-of-concept of how to learn to play piano with a real world robotic hand. Specifically, we employ a Sim2Real approach where we first train a policy in simulation, and following we deploy it on the real world dexterous hand. Experimental results show that the learned policy can play several different pieces with satisfying musical results. Nonetheless, there is still a long way before we can achieve in robots the same level of proficiency and elegance of human pianists. Beyond the artistic *raison d'être*, we believe that playing piano is a relevant and challenging benchmark for dexterous contact-reach manipulation, and advances in this task can be more widely relevant for the whole manipulation community.

ACKNOWLEDGMENTS

We thank Ken Nakahara for the support and tips regarding operating the robotics. This work was partly supported by the German Research Foundation (DFG, Deutsche Forschungsgemeinschaft) as part of Germany’s Excellence Strategy – EXC 2050/1 – Project ID 390696704 – Cluster of Excellence “Centre for Tactile Internet with Human-in-the-Loop” (CeTI) of Technische Universität Dresden, and by Bundesministerium für Bildung und Forschung (BMBF) and German Academic Exchange Service (DAAD) in project 57616814 (SECAI, School of Embedded and Composite AI).

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APPENDIX

A. The Reward Formulation

The total reward consists of four parts

$$r_{\text{total}} = r_{\text{energy}} + r_{\text{hand_position}} + r_{\text{keypress}} + r_{\text{sliding}},$$

each rewarding a certain behavior of the agent.

The r_{energy} reward penalizes fast movements, that need a lot of force. Further, it avoids oscillations of fingers that don't lead to higher rewards. The energy reward also leads to a policy that behaves more fluently, which makes it more human-like.

$$r_{\text{energy}} = -|\tau_{\text{joints}}^T|v_{\text{joints}}| * C_{\text{energy}}$$

The implementation is the same as used in the robopianist environment [18], where τ_{joints} contains the torques of each active joint and v_{joints} contains the velocities of each joint. C_{energy} is the energy coefficient and is a hyperparameter of the environment. Unless otherwise specified $C_{\text{energy}} = 0.12$.

The reward $r_{\text{hand_position}}$ is designed to guide the hand towards targeted keys. This is achieved by reducing the average distance between the palm of the hand and the targeted keys.

$$r_{\text{hand_position}} = \frac{1}{|P_{\text{targets}}|} * \sum_{p_{\text{key}} \in P_{\text{targets}}} g(\|p_{\text{key}} - p_{\text{palm}}\|_2)$$

The distances are bounded between 0 and 1 using the *tolerance* function of the *dm_control* library [14], notated as g . Further is P_{targets} , the set of the cartesian positions of all targeted keys, and p_{palm} represents the cartesian position of the palm.

The r_{keypress} reward is the most important part of r_{total} because it encourages the agent to press the correct keys. The reward is designed based on two design requirements:

- 1) Pressing no keys should be worse than pressing the wrong keys.
- 2) Pressing the correct keys should be better than pressing the wrong keys.

Those requirements lead the exploration of the model towards pressing the correct keys without being "afraid" of pressing the wrong keys. This relationship is implemented by using multiple cases depending on the currently pressed keys:

For $k_{\text{target}} > 0$ we divide the keypress reward into tree cases

$$r_{\text{keypress}} = \begin{cases} 0 & , k_{\text{wrong}} = 0 \wedge k_{\text{correct}} = 0 \end{cases} \quad (1)$$

$$r_{\text{keypress}} = \begin{cases} 0.5 + 0.5 * \bar{\mu}_{\text{target}} & , k_{\text{wrong}} > 0 \end{cases} \quad (2)$$

$$r_{\text{keypress}} = \begin{cases} 1 + 0.5 * \bar{\mu}_{\text{target}} & , k_{\text{wrong}} = 0 \wedge k_{\text{correct}} > 0 \end{cases} \quad (3)$$

For $k_{\text{target}} = 0$ is the reward calculated as follows:

$$r_{\text{keypress}} = 2 * (1 - \max_{\mu' \in \mu_{\text{wrong}}} \mu') \quad (4)$$

The cases (1), (2) and (3) assume that at least one key should be pressed at the current timestep, while the case (4) defines the reward when no key is meant to be pressed. The cases are separated based on the currently pressed keys of the piano. For this purpose, the variable k refers to a number of keys. More precisely:

- k_{target} : How many keys are meant to be pressed?
- k_{wrong} : How many keys are pressed that are **not** meant to be pressed?
- k_{correct} : How many keys are pressed that are meant to be pressed?

Further, $\mu \in [0, 1]$ refers to the normalized state of the key with $\mu = 1$ representing a completely pressed key.

- $\bar{\mu}_{\text{target}}$: The average state of all targeted keys.
- μ_{wrong} : The set of the states of all the pressed keys that are not meant to be pressed. This also implies that $|\mu_{\text{wrong}}| = k_{\text{wrong}}$.

Relating the cases to the design requirements reveals that case (2) should yield a greater reward than case (1). This condition is satisfied, as case (2) always yields a positive value, whereas case (1) is always zero. The second design requirement specifies that case (3) should yield more reward than case (2). This can be demonstrated by calculating the difference between the two cases: $(3) - (2) = 1 + 0.5 * \bar{\mu}_{\text{target}} - (0.5 + 0.5 * \bar{\mu}_{\text{target}}) = 0.5 > 0$. Since this difference is always positive, case (3) indeed provides a greater reward than case (2), meeting the design requirement.

The r_{sliding} reward is designed to penalize fast sideways movement of the hand while keys are pressed. This avoids the local optimum where one finger is pressed statically while the hand slider "selects" the key. The penalty is doubled if two adjacent keys are pressed, which is unavoidable while sliding sideways.

$$r_{\text{sliding}} = -\lambda * v_{\text{hand}}^2 * 3$$

The $\lambda \in \{0, 1, 2\}$ represents how many adjacent keys are pressed simultaneously. $\lambda = 0$ is the case if no keys are pressed, $\lambda = 1$ is the case when no adjacent keys are pressed and $\lambda = 2$ is the case when adjacent keys are pressed. Note that the current speed of the hand v_{hand} is squared. This allows for slow hand movements, while fast movements are more strongly penalized.

The values of $\lambda \in \{0, 1, 2\}$ indicate the number of adjacent keys pressed simultaneously. Specifically, $\lambda = 0$ represents no pressed keys, $\lambda = 1$ corresponds to non-adjacent keys being pressed, and $\lambda = 2$ denotes that adjacent keys are pressed. Additionally, the current hand speed v_{hand} hand is squared, allowing slower hand movements to receive less penalty, while faster movements receive a stronger penalty. The whole term is multiplied by three to increase the effect of this penalty.