A Human-Computer Duet System for Music Performance

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ABSTRACT
Virtual musicians have become a remarkable phenomenon in the contemporary multimedia arts. However, most of the virtual musicians nowadays have not been endowed with abilities to create their own behaviors, or to perform music with human musicians. In this paper, we firstly create a virtual violinist, who can collaborate with a human pianist to perform chamber music automatically without any intervention. The system incorporates the techniques from various fields, including real-time music tracking, pose estimation, and body movement generation. In our system, the virtual musician’s behavior is generated based on the given music audio alone, and such a system results in a low-cost, efficient and scalable way to produce human and virtual musicians’ co-performance. The proposed system has been validated in public concerts. Objective quality assessment approaches and possible ways to systematically improve the system are also discussed.

CCS CONCEPTS
• Applied computing → Performing arts; Media arts; Sound and music computing.

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Figure 1: Illustration of the automatic concert animation system.

KEYWORDS
Automatic accompaniment, body movement generation, animation, computer-human interaction, music information retrieval.

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1 INTRODUCTION
Let’s imagine a music concert, where a human musician sits on the stage and performs a duet together with a virtual musician on the screen. The virtual musician can move its body by itself. Its right hand takes a bow to play a virtual violin. Its right hand moves up and down in a way similar to that a real violinist plays the music piece. The virtual musician also follows the human musician’s tempo, and make the two voices of the duet to be synchronized and harmonized. All these behaviors of the virtual musician are automatically generated or triggered simply from the music: once the concert program is determined, the human musician can practice, rehearse, and perform music with the virtual musician like with a real human, by simply following the music content (see Figure 1).

The concept of virtual musician, or more broadly speaking, virtual human character, has become increasingly popular in the past few years. Virtual musicians and related performance types have unlocked great potential in social media and interactive multimedia arts. Virtual idols such as Hatsune Miku [1], Luo Tianyi [2], and thousands of on-line VTubers play music either on live streaming

1https://www.bbc.com/worklife/article/20181002-the-virtual-vloggers-taking-over-youtube
platforms or in real-world venues, sometimes even interacting with human musicians [3]. Some of the performance videos have even earn them millions of view counts. As the venues and audiences of virtual music performance are both scaling up, it is expected that a low-cost, personalized, and automatic system which can animate virtual musicians’ performance according to the music content, and enforce the interaction between human musicians and virtual ones will be in urgent need.

For most of the personalized performance animation tools such as the Character Animator CC and many others on making virtual characters, real-time motion capture is employed to capture a human character’s facial and body movement data, and rigging technique is then used to convert such data into the virtual character. Being efficient for small-scale production, such a workflow is however limited in producing the content that scales, for example, music performance. As Figure 1 shows, a music performance usually incorporates two or more instrument tracks. Recruiting human musicians specialized on various instruments to perform music pieces for every new production is tedious and inefficient. Building a full-interaction mechanism between human and virtual musicians in during music performance is also a less noticed topic; in most of the human-computer collaborative performance, the music is performed simply with a fixed tempo, i.e., in karaoke mode [4].

Recently, performance animation without the aid of human characters has caught attention. Animation can be generated from texts, voice, and music. For example, music-to-body-movement generation techniques are expected to solve the difficulty in obtaining professional musicians’ motion data; this technique aims at mapping a music recording (usually a solo with known instrument type) into a skeleton sequence, and this sequence represents a reasonable movement of a human musician in playing the same music piece with the same instrument. Recently developed motion generation models have shown great potential in generating the movements of violinists and pianists. With such techniques, motion data for animating the virtual musician can be generated directly from the music content, without the need to have human musicians to record the motion data.

Enforcing the interaction between human and virtual characters during music performance is needed not only in animation. Rather, it has been widely discussed in music information retrieval, robotics, new interfaces for music expression, and multimedia arts. For example, score following and automatic accompaniment systems utilize real-time audio tracking algorithms to make a computer perform accompaniment following the human musician’s expressive tempo. Alternatively, human musicians also use their body movements, sounds, or physiological signals to trigger, control, and manipulate the virtual musician’s sound or actions. Providing high flexibility for artists to design the audio, visual, and interactive effects in the performance, the latter approach however requires the installation of various kinds of sensor devices and data collection systems, and is less suitable for low-cost production such as the performance of an individual VTuber.

In this paper, we focus on the incorporation of automatic animation and real-time music tracking techniques into a virtual musician system. In our proposed system, the human musician and virtual musician communicate with each other by means of music itself, without intervention from manual control or sensor data. Particularly, we emphasize the following three contributions: 1) the virtual musician’s behaviors are automatically created from music, 2) the only data required to trigger the interactive music performance is the music content itself, and 3) evaluation metrics for quality assessment on interaction and generation results can be given for further development. We focus on the scenario of human-computer duet, as shown in Figure 1, where a human pianist plays duet with a virtual violinist. To the best of our knowledge, this work represents the first attempt to bridge the technical gaps among automatic accompaniment, music-to-body-movement generation, and animation.

The rest of this paper is organized as follows. Section 2 gives a review on the techniques related to human-computer duet, automatic animation, and interactive multimedia arts. Section 3 describes the whole system. Technical details of real-time music tracking and body movement generation are described in Section 4 and Section 5, respectively. After that, Section 6 deals with the integration part, including model binding and performance rendering. Real-world demo records and quality assessment of the system are reported in Section 7. Finally, we conclude our work in Section 8.

2 RELATED WORK

Our review of the related work mainly focuses on real-time music tracking and automatic animation, the two critical techniques to characterize the proposed virtual musician system.

2.1 Real-time music tracking

There are three ways to synchronize human’s and machine’s performances on live. The first way is letting human follow machine’s tempo (usually a constant tempo), and the second way is letting machine follow human’s tempo (usually an expressive tempo varying with time and with performance). The first two ways can both be combined with the third one, that utilizes specific gestures, sounds or sensor signals as flag events to re-synchronize the performance [4, 14]. The first way guarantees a stable performance, while the second way, usually known as the automatic accompaniment technique, provides great flexibility for human’s interpretation of music during performance. Since its first appearance in the 1980s [15], automatic accompaniment has been widely studied in various scenarios. Methods for music tracking include state-space models such as Hidden Markov Models (HMM) [16], Monte Carlo inference [17], and particle filters [18]; dynamic time warping (DTW) models such as online DTW (ODTW) [8, 9, 19], windowed DTW (WTW) [20]; and parallel DTW (PDTW) [21–23], and also reinforcement learning approaches [24]. It should be noted that real-time music tracking has been well-developed technology on MIDI data, but is still highly challenging on audio data an on various classes musical instruments, as the tracking results are sensitive to the variation of audio features. Therefore, developed systems and products for audio-based real-time music tracking are still rarely seen, except for some examples such as Antescofo’s Metronaut, which is targeted for automatic accompaniment in music practice.
A number of metrics have been proposed to evaluate a real-time music tracking system. These metrics are mostly based on measuring the latency/ error of every note event [25–27], or calculating the number of missing/ misaligned note during the process of score following [8, 26, 28]. There are, however two major issues in such evaluation methods. First, the performance of score following cannot fully represent the performance of a automatic accompaniment system operating in real-world environments, as it ignores the latency introduced in sound synthesis, data communication, and even reverberation of the environment. Second, note-level evaluation is suitable only for hard-onset instruments such as piano, while it is limited for soft-onset instruments such as violin, as the uncertainty of violin onset detection could propagate errors in the final evaluation results. To solve these issues, we firstly propose an experimental setup which allows evaluation of the system in a real-world environment. Further, we provide frame-level evaluation approach for general types of instrument, with intuitive visual diagrams that demonstrate how the system interacts with human during the performance.

In the following of this paper, we use the term human-computer duet or real-time music tracking when referring to the automatic accompaniment technique. The reason we avoid using the term “auto accompaniment” is that in our scenario, the machine’s (virtual musician’s) role is not limited to accompaniment; the virtual musician can play either accompaniment or main melody.

2.2 Automatic animation
Performance animation tools employ motion capture and model rigging technology to create animated characters that mimics specific human performances [29–32]. New developments that support multi-modal input such as texts, voice, and music to automate the workflow of performance animation have also received wide attention. For text-to-animation tasks, linguistic rules and action representations are derived from screenplays and then are used to generate pre-visualization in animation [33]. The recently proposed TakeToons system achieves efficient animation by incorporating motion capture with a story model, the latter is learned from the scripts with annotation of relevant events such as character actions, camera positions, and scene backgrounds [34]. For video-to-animation tasks, a recent work further applies pose estimation and clustering technique to convert a video into 2-D animation [35]. For audio-to-animation tasks, animation is synthesized based on mimicking onomatopoeia sounds with audio event recognition techniques [36]. The generative adversarial network (GAN) is also applied to convert conversational speech signals to gestures [37].

Several attempts have also been devoted to generate body movement from music. [5] used a recurrent neural network (RNN) to encode audio features and then a fully-connected (FC) layer to decode it into the body skeleton keypoints of both pianists and violinists. In [38], choreographic movements are generated from music according to the user’s preference and the musical structural context, such as the metrical and dynamic arrangement in music. A recent work considered modeling the violinist’s body movement with individual parts, including right-hand bowing, left-hand fingering, and the expression of the whole upper body [6]. Another recent work on pianists’ body skeleton generation [7] also considers musical information including bar and beat positions in music. The model combining CNN and RNN was proven to be capable of learning the movement characteristics of each pianist.

The method for assessing the quality of music-to-body-movement generation is still an open problem, mainly because the mapping from music to motion is not one-to-one. Subjective tests has been conducted, and the questions to participants are how reasonable and how natural the generated body movement behaves with music [6]. A commonly-used objective metric is the distance between the predicted keypoints and the keypoints estimated by pose estimation algorithms in the original videos, the latter is taken as the pseudo-ground-truth [5]. Recently, the accuracy of bowing attack is proposed specifically for evaluating the quality of virtual violinists’ body movement. Another issue in this task is that there is no unique ground truth. In this paper, we argue that creating a testing data with multiple versions of ground truth (e.g., multiple performance videos for the same music piece) could represent a further step to analyze the result of the body movement generation models.

3 SYSTEM OVERVIEW
Figure 2 illustrates the system diagram of the proposed human-computer duet system. In the description below, we refer to the person who prepares the music pieces to be performed as a director, and the person playing music with the virtual musician as a performer or a human musician. While it is possible for a user to serve both of these roles, we distinguish them to clarify different working stages in our system. A MIDI or a MIDI-synthesized audio specifying exact note events is named as a reference. A recording of a music performance made in the preparation stage (i.e., the offline stage) is referred to as a recorded or rehearsed performance. The performance happening in the scene is referred to as live performance.

The proposed system is built upon the mechanism to synchronize altogether the reference, rehearsed, and live contents. First, a director select a music piece to be performed. In our discussion, the music piece contains a reference violin track and a reference piano track, both of which are perfectly aligned with each other. To achieve better music tracking during performance, the performer may prepare a piano recording of her or his own. This recording pertains the performer’s traits of music better than the reference MIDI does. The reference and performed piano are aligned using the offline DTW algorithm such that the temporal correspondence between both recordings can be retrieved directly. In live performance, the real-time music tracker follows the live piano played by the performer, and by the online DTW (ODTW) alignment, it monitors the current position on the reference tracks. The music tracker then triggers the visual animation and sound synthesis items to generate the body movement and sound of the virtual musician’s live violin performance at the current position.

As for automatic animation, there are two possible ways to generate the virtual violinist’s motion. The basic way is employing pose estimation [39] to extract pose sequence on a violin video recording of the selected music piece for animation. The advanced way is applying music-to-motion generation techniques, where the motion generation model is trained on a music video dataset of violin performance. With this model, a pose sequence can be generated from the reference violin audio, which is aligned with the reference violin MIDI in order to directly synchronize with the
piano signal in live performance. The generated body skeleton is bound with a 3D human rigged model and a violin model for character animation. According to the real-time tracking result with the live piano audio, the virtual musician’s audio and video parts corresponding to the performance are rendered with a real-time sound synthesizer and an animator. The details of these building blocks will be introduced in the following sections.

4 REAL-TIME MUSIC TRACKER

In this section, we review the DTW and ODTW algorithms, and describe the implementation of the real-time music tracker.

4.1 Dynamic time warping

Given \( X := \{x_p\}_{p=1}^P \) and \( Y := \{y_q\}_{q=1}^Q \), the features extracted from any two sequences mentioned in Section 3 and Figure 2. Each \( x_p \) and \( y_q \) are the \( p \)th and \( q \)th feature vectors of \( X \) and \( Y \), respectively. The DTW algorithm finds the path \( \mathcal{W} := \{(p_k, q_k)\}_{k=1}^K \), \( 1 \leq p_k \leq P \) and \( 1 \leq q_k \leq Q \), such that the total alignment cost \( \sum_{k=1}^K d(x_{p_k}, y_{q_k}) \) is minimized, where \( d(x_{p_k}, y_{q_k}) \) is the Euclidean distance between \( x_{p_k} \) and \( y_{q_k} \). The path \( \mathcal{W} \) therefore represents the optimal mapping from \( X \) to \( Y \). The optimal alignment path can be found by dynamic programming. The cumulative cost matrix \( D \in \mathbb{R}^{M \times N} \) is calculated recursively as follows:

\[
D[p_k, q_k] = d(x_{p_k}, y_{q_k}) + \min \begin{cases} 
D[p_k - 1, q_k] \\
D[p_k - 1, q_k - 1] \\
D[p_k - 1, q_k - 1]
\end{cases} 
\]

(1)

\( D[p_k, q_k] \) stands for the minimum of total cost of the alignment path from \((1, 1)\) to \((p_k, q_k)\). After \( D \) is calculated, we backtrack the matrix from \( D[P, Q] \), find each optimal step iteratively and get the optimal alignment path \( \mathcal{W} \).

The conventional DTW assumes that the whole recordings of both sequences are known in advance. This is however not the case in live performance, for it is impossible to retrieve the performance content in the future. Besides, the quadratic complexity of DTW limits the algorithm from real-time computation. The ODTW algorithm [19] is proposed to solve these problems with two main modifications: first, instead of computing the cost matrix \( D \) from all \((p, q) \in [1, P] \times [1, Q]\), the time intervals considered in computing \( D \) is dynamically determined by the warping path direction and a search depth with a fixed length \( c \). Second, instead of finding the optimal path \( \mathcal{W} \) in the backtracking process after knowing the complete cost matrix, the path at the \((k + 1)\)th time step is determined right after \( D[p_k, q_k] \) is known. This is controlled by another parameter, which resets the direction of warping path when it has been stuck into one direction for a certain time steps. As a result, ODTW achieves the performance in linear time and space. See [19] for the details of the ODTW algorithm.

4.2 Implementation details

The real-time music tracker we employed is a re-implementation of the ‘Any time’ music tracker by Arzt and Widmer [8, 9]. The tracker operates in multiple threads, where each thread is in charge of a sub-task. The sub-tasks include a music detector, a rough position estimator, several ODTW trackers and a decision maker, as shown in Figure 3. These components enables an automatic way to trigger the tracking mechanism when the performance begins, and track the performance continuously with the computing cost affordable for a laptop. The audio features of both the live and the rehearsed piano signals are the rectified spectral difference, which is the first-order difference of spectrum with the negative elements set
to zeros. The feature is derived from the log-frequency spectrum which frequency resolution is one semitone and time resolution is 20ms. Two types of features with low and high temporal resolutions are employed. The high-resolution feature for the ODTW trackers is the above-mentioned spectral difference, and the low-resolution feature for the rough position estimator is a downsampled version of the high-resolution spectrum.

The music detector identifies the time instance that the performance starts and tells the system to start tracking. The music detector is implemented in a simple yet practical way: we use the conventional DTW to align the live audio with the first 0.5 sec of the rehearsed audio. If the alignment cost is lower than a preset threshold, the music detector triggers the music tracking process.

The rough position estimator returns a set of possible current positions the live piano signal corresponding to the rehearsed piano. This is done by computing the similarity (measured by the Euclidean distance) of the latest nine seconds of the live audio to the segments of the rehearsed audio ending at any positions. The positions which reach high similarity are taken into the set of possible current positions. In [8, 9], the rough position estimator keeps all possible positions to deal with cases where the music might jump to any position on the score in cases like practice or improvisation. In our case, since we use a rehearsed audio, such jumps are unlikely to occur. We keep using the rough position estimator just for faster correction when the ODTW trackers have wrong alignment.

In the tracking process, the ODTW algorithm is utilized to align the high-resolution features of live piano and the rehearsed piano. Multiple ODTW threads work in parallel, and each thread deals with a possible current position estimated by the rough position estimator. In addition to the precise estimation of current position, the cumulative alignment cost and instantaneous tempo of the live audio is also recorded. These results of all the ODTW threads are then fed into the decision maker for final decision of the current position. In practice, we use about 2-4 ODTW threads in the system, depending on the available hardware resource.

Finally, the decision maker selects an ODTW thread as the trusted one and output the tracking result of that selected ODTW thread. This is done by finding the minimal cumulative cost value of the currently selected ODTW threads to all the other ODTW threads. As new audio frames received, the decision maker repeats these procedures and updating output with the credible ODTW matcher. The real-time music tracker is implemented in Python 3.7 with the multiprocessing package for parallelization.

5 BODY MOVEMENT GENERATION

As discussed in Section 3, the virtual musician’s body movement for music performance is obtained with two approaches: pose estimation and body movement generation. The latter approach requires a dataset with audio and pose contents of violin performance to model the music-to-body-movement correspondence. For pose estimation in both the approaches, we adopt [39] to extract the 3-D position of the violinists’ 15 body joints, resulting in a 45-D body joint vector for each time frame. The joints are extracted frame-wise at the video’s frame rate of 30 fps. All the joint data are normalized such that the mean of all joints over all time instances is zero. The normalized joint data are then smoothed over each joint using a median filter with a window size of five frames.

For body movement generation, we extend the framework of audio-to-body (A2B) dynamics [5], a 2-D body movement generation framework, into a 3-D body movement generation framework, as illustrated in Figure 4. The framework is constructed by a RNN with long-short-term memory (LSTM) units plus a FC layer. The input audio features extracted from the recorded violin are first fed into the RNN. The output values of the RNN are then fed into the FC layer. To model the long-term dependency between music and body movement, a delay mechanism between the input and output is introduced [5]: the model takes input audio feature at time $t$ and outputs the skeleton data at $t - \eta$. In this paper, we set $\eta = 6$ frames.

The input audio features are the 128-D mel-spectrogram with a temporal resolution of 1/30 sec. In this way, the audio and skeletal features for training are synchronized. All the features are extracted with the librosa library [40]. Each training sample is segmented at the downbeat positions, as we consider such structural information as a guide of the corresponding body movement. To do this, we first annotate beat position on the MIDI file of each musical piece, and then use DTW to align beat position between the MIDI-synthesized audio and the recorded audio performed by human violinists. As a result, each training sample starts from a downbeat and is with length of 300. All the segmented data are normalized by z-score. The model is trained by minimizing the $L_1$ loss between the output and the ground-truth skeleton sequence. The hidden unit of LSTM is 200, followed by dropout 0.1, and the model is optimized by Adam with $\beta_1 = 0.9, \beta_2 = 0.98, \epsilon = 10^{-5}$, and learning rate is set to 0.001.

6 MODEL BINDING AND ANIMATION

The next step to launch the animation is to bind the generated skeleton data to the 3-D human rigged model (called skeleton binding) and also to the violin model (called violin binding). The model binding and the animation processes were done with the cross-platform game engine, Unity 3D 2018.3.

6.1 Skeleton and violin binding

We use the Humanoid5 provided by Unity as our 3-D human rigged model. The skeleton data obtained from either pose estimation or body movement generation are in very limited resolution, and with noisy movement and sporadic articulation. To avoid unstable body movement during animation, we consider applying the inverse kinematics (IK) method to bind the motion data with the

5https://docs.unity3d.com/Manual/AvatarCreationAndSetup.html
rigged model with refined skeleton joint positions. In comparison to forward kinematics (FK) which directly assigns all the skeleton joint rotation values to the model, IK allows one to infer the whole skeleton joint data from only the skeleton joints which are either more significant for violin performance (e.g., the upper body and hands), or better estimated by the pose estimation or body movement generation models. The resulting skeleton data obtained from the IK equations therefore become more smoothed and reasonable. In this system, we consider four joints for IK inference: left shoulder, left hand, right shoulder, and right hand. The base of the spine is taken as the center of body rotation. The system is implemented with the Full Body Biped IK algorithm\textsuperscript{6} in Final IK\textsuperscript{1.9}, which is provided by the Unity Assets Store.

The violin model has two parts: the violin body and the bow. Figure 5 illustrates the coordination of the violin model. For the violin body, the origin of coordinates is at the bottom of the chinrest, with the $y$-axis toward the scroll, and the $z$-axis perpendicular to the frontal plane of the violin body. The origin of coordinates is placed in the middle of the violinist’s left shoulder and neck, making the $y$-axis of the violin body be connected to the left hand joint. For the bow, the origin of coordinates is at the bow frog and is connected to the right hand joint. The bow stick is placed in the $y$-axis. The $y$-axis of the bow is also connected to a position in between the bridge and fingerboard of the violin body. The position and angle of the violin body and bow are updated every time after the skeleton is updated with IK.

\subsection{6.2 System integration}

To ensure system stability for real-world performance, we distribute the on-line computing counterparts described in Section 4, 5, and 6.1 into two laptops: one laptop takes charge in real-time music tracking, and the other one takes charge in automatic animation; see Figure 7. The two laptops communicate with each other through a local network: during a performance, the real-time music tracker continually sends the newest tracking result (i.e., the corresponding time of the rehearsed piano audio that matches the live piano), which is packed in JSON format, to the automatic animator on the other laptop through the User Datagram Protocol (UDP). The skeleton data generated from the rehearsed violin and the MIDI of reference violin are both pre-stored in the automatic animator. We use Ableton Live to play the sound, and Unity to display the visual content of violin performance. The real-time music tracker sends a UDP package to the automatic animator every 20ms. The automatic animator receives it and manages two tasks. First, it guides the sound synthesizer to play the violin performance from MIDI, according to the received tracking results, such as to make the violin performance synchronized with the live piano. Second, it guides the animator to display the virtual violinist’s body movement, which also follows the newest tracking result.

\section{7 RESULTS}

The proposed human-computer duet system can be properly set in a performance venue, as shown in Figure 6. The system has been publicly demonstrated twice. The first one was at the faculty lounge of the authors’ Institute, where around 20 people watched the demo. The second one was in a public, ticket-selling concert held in a famous experimental music venue located in the authors’ city, where 120 people attended the concert. Detailed information

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure5.png}
\caption{The coordinate setting for violin binding. Left: the violin body. Right: the bow.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure6.png}
\caption{The setting of the human-computer duet system. Note that to verify the robustness of the real-time music tracking unit, the sound of live piano for music tracking is collected by a microphone (at the right of the photo) rather than collected by line-in.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure7.png}
\caption{The distributed experiment setting of the computer-human duet system. The two laptops shown below are for performance, and the third laptop shown above is for recording only.}
\end{figure}
of these activities are hidden for double-blind review. The music piece we chose to perform and test on is Violin Sonata No.5, Op.24 (Spring), movement I. Allegro by Ludwig van Beethoven. The system works stably over the whole performance, which lasts for around 10 minutes. The recordings of the public demo and concerts are attached in the supplementary materials.

We received the audience’s responses saying that the performance was insightful and they would like to join in again if similar kinds of concerts will be held in the future. However, we still regard the objective evaluation as a more precise way to assess the quality of the system. In the followings, we describe our proposed quality assessment approach, and discuss the ways to improve the system based on the assessment results.

### 7.1 Assessment of real-time music tracking

We propose a novel method to evaluate the performance of real-time music tracking from real-world performance. The idea is to evaluate the deviation between online music tracking and offline alignment with the live recording. The process is described as follows:

1. Record the live piano and live violin audio with a multi-channel recording device; see Fig. 7. Confirm that the reference piano (blue circles in Figure 8) MIDI and reference violin MIDI (red circles in Figure 8) are perfectly synchronized.

2. Obtain the time mapping between the recorded live piano and the reference piano MIDI with offline synchronization (see the dashed lines connecting the blue circles and the light blue circles in Figure 8). According to such a temporal mapping, one can synthesize the estimated violin signal, which is the ‘expected’ violin performance with the live piano; see the gray circles in Fig. 8. The estimated violin is taken as the benchmark for a music tracking system.

3. Obtain the time mapping between the live violin and the estimated violin with offline synchronization. If the time $t_i$ of the live violin is mapped to $t_j$ of the estimated violin, then the latency of the real-time music tracking system performing the music piece at $t_i$ is defined as $\Delta[t_i] := t_j - t_i$.

![Diagrams and figures](image-url)

Figure 8: A conceptual illustration of evaluating the real-time music tracking system on a sample in 120 BPM. Circles denote beat positions, and the circles connected with a vertical dashed line are synchronized. Note that the synchronization result determines how the violin part should be played (i.e., the estimated violin part).

In other words, positive latency values mean that the music tracker drags and negative latency values means that the music tracker rushes. Besides the instantaneous latency values, we also consider the average deviation of a music piece, defined as $(1/T) \sum_i |\Delta[t_i]|$, which is the average over the absolute values of the latency at every time step.

As shown in the upper-right part of Figure 7, we used one more laptop, which records both the audio streams (i.e., live piano and live violin) in the live performance. An 8-channel audio interface, Zoom UAC-8, and a robust Digital Audio Workstation (DAW), Logic Pro X, are utilized to support synchronized multi-channel recording. The live piano and the reference piano MIDI are synchronized in
terms of beat positions. To do this, we employ the beat tracking tool madmom [41] to get the beat positions in second for both the live and reference piano. Then, the reference piano MIDI is adjusted to fit the beat positions of the live piano. As a result, the adjusted MIDI nicely synchronizes the live piano audio. The estimated violin and the live violin are synchronized with conventional DTW. The madmom library is not used here because the beat tracking algorithm performs less accurate for violin signals. The sound of estimated violin is also synthesized with the timbre same as with the live violin. This is to ensure stable performance of DTW synchronization with consistent audio features of both tracks. We use the chromagram features extracted from the librosa library for DTW synchronization.

To evaluate how the proposed system reacts under different performance speeds, we tested the system on four different ways in performing the first 25 bars in the Spring Sonata: 1) normal speed (115-145 bpm), 2) slow speed (90-120 bpm), 3) fast speed (135-175 bpm), and 4) accelerando speed starting with around 80bpm and ending with 160 bpm. Figure 9 shows the system’s latency over time by how many 16th notes the live violin delays or leads the live piano/estimated violin. For example, in Figure 9 (b), when the human pianist starts at a relatively slow speed of 100bpm, the live violin played faster than the benchmark (i.e. live piano) in the beginning by about four 16th notes, which is about one beat of leading. Such a situation goes stable at around the fifth measure. Similarly, in Figure 9 (c), when the human pianist starts at a relatively fast speed of 150bpm, the live violin falls behind in the beginning, but also get synchronized after the fifth measure, where the latency values within one 16th note can be observed. In summary, for all the four cases, it takes the system around four measures to get synchronized with the live piano, and once it gets synchronized with the human musician, the deviation can be found within ±0.25 beats. We can also observe that an abrupt change of speed does not always imply a change of latency. In fact, latency is also related to the structure of music; for example, the latency values for the four cases are relatively unstable at around the 15th measure, where the piano part is the main melody in a rapid note sequence. These unstable parts increase the average deviation for each music sample and cause few but clear mismatch, as demonstrated in the supplementary video.

### 7.2 Assessment of body movement generation

The model is trained and validated on a recorded dataset containing 140 violin solo videos with total length of 11 hours. These videos are from 10 college students who major in violin. 14 violin solo pieces was selected to be performed by the 10 students; that means, each violin solo piece has 10 versions in the dataset. The details of this dataset will be announced afterwards.

For training, we first select the videos from one of the violinists, and conduct a leave-one-piece-out (i.e., 14-fold cross validation) scheme to train the 14 models. Each model is evaluated on the left-out piece (for that fold partition) performed by the remaining nine violinists. The results are then the average over the nine violinists. That means, our evaluation strategy benefits from multiple versions of each music piece in the dataset.

Two metrics, $L_1$ distance and bowing attack F1-score, are used for quality assessment. $L_1$ distance is simply the distance between the generated and the ground-truth joints. In the practice of music performance, a bowing attack is the time instance when the bowing direction changes (i.e., from up-bow to down-bow or from down-bow to up-bow). In other words, bowing attack is an important feature regarding how reasonable the generated body movement is. The bowing attack of the ground truth and the generated results can therefore be estimated by the first-order difference of the right-hand wrist joint sequence. By abuse of this definition, we define a bowing attack in the $x$, $y$, or $z$ direction as the time instance that the right-hand wrist joint changes its direction in the $x$, $y$, or $z$ direction, respectively. For a ground-truth bowing attack at $i$, a predicted bowing attack is a true positive if it is in the interval of $[i - \delta, i + \delta]$. If there are two or more predicted bowing attacks in that interval, only one of them is regarded as true positive and others are regarded as false positive. After identifying all the true positive, false positive, and false negative, the F1-scores for the bowing attack in the three directions can be reported. In this paper, we set $\delta = 1$ frame, i.e., $1/30$ seconds.

The average $L_1$ distance is 0.0393; to be more specific, it is around 30% of the lower arm length (average value = 0.13). Table 1 lists the resulting F1 scores of bowing attack and the average over the three directions, compared to the baseline results, which take naive guess by taking all beat positions as the bowing attack (denoted as ‘beat’ in Table 1). We observe that the F1-scores are much better than the baseline, which shows the effectiveness of the model. The F1 score in the $y$-direction performs better than others, since the actual bowing direction is mainly in the $y$-axis (the front-back direction of the violinist). To understand the actual quality of these results more, in the supplementary material we compare two animation results, one using the skeleton of pose estimation from a rehearsed video, and the other using the skeleton generated from the body movement generation model. It shows that the deviation of the right hand position and the timing of the bowing attack are the two issues that still have room for improvement, which are consistent with the quantitative experiment results.

### 8 CONCLUSION

A virtual musician system supporting human-computer duet from audio has been implemented. We have accomplished fully automatic real-time tracking and virtual performance, both controlled by music audio only. By integrating all the novel techniques together, we then reexamine the limitation of these techniques at a higher level, such as the mismatch of the duet performance at the beginning of the performance, and the instability of the end-to-end body movement generation method, both of which cannot be observed with simplified evaluation metrics. These provide new insights and possible ways to improve the system, such as incorporating an online feedback mechanism to suppress abrupt change of tracking position, and combining end-to-end rigging and motion generation model such as rignet [42] for more precise animation. Demo videos, supplementary materials, and acknowledgement can be seen at the project website: https://sites.google.com/view/mctl/research/automatic-music-concert-animation
