AN INTEGRATED SYSTEM ARCHITECTURE FOR GENERATIVE AUDIO MODELLING

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ABSTRACT

We introduce a new system for data-driven audio sound model design built around two different neural network architectures, a Generative Adversarial Network(GAN) and a Recurrent Neural Network (RNN), that takes advantage of the unique characteristics of each to achieve the system objectives that neither is capable of addressing alone. The objective of the system is to generate interactively controllable sound models given (a) a range of sounds the model should be able to synthesize, and (b) a specification of the parametric controls for navigating that space of sounds. The range of sounds is defined by a dataset provided by the designer, while the means of navigation is defined by a combination of data labels and the selection of a sub-manifold from the latent space learned by the GAN. Our proposed system takes advantage of the rich latent space of GAN that consists of sounds that fill out the spaces "between" real data-like sounds. This augmented data from GAN is then used to train an RNN, that has the capability of immediate parameter response, and generation of audio over unlimited periods of time. Furthermore, we develop a self organizing map technique for "smoothing" the latent space of GAN that results in perceptually smooth interpolation between audio timbres. We validate this process through user studies. Our system contributes advances to the state of the art for generative sound model design that include system configuration and components for improving interpolation and the expansion of audio modeling capabilities beyond musical pitch and percussive instrument sounds into the more complex space of audio textures.

1 BACKGROUND AND MOTIVATION

Sound modeling for the purpose of synthesis is still mostly a manual programming process. It is labour intensive, costly, and the implementation is done by specialists other than end users of the systems. The overarching objective of this work is to provide a means for instrument and sound designers to create interactive sound generators by merely providing data samples from a sound space and specifications for how they want to navigate that space.

We use the term "sound model" rather than "synthesizer" in part to emphasize the process of their creation, but also because synthesizers are typically designed to produce as wide a range of sounds as possible. Sound models are more targeted, and have two essential components: a constrained range of sounds they are capable of producing, and an *expressive* means of navigating that space via parametric control.

A sound model for our purposes also meets several "playability" criteria. One is that parameters can be changed at arbitrary times. Next we define the Parameter Response Time (PRT) as the number of time steps for sound generation to adapt to changes in the input or conditioning parameters. Playability requires perceptually negligible PRT. A playable sound model should also be capable of generating sound for an unlimited period of time. It further requires an understandable mapping between changing control parameters and their effect on sound. We operationalize this notion to mean (a) that different parameters pertain to different perceptual dimensions, and (b) that their affect on perceptual changes in sound are approximately linear or at least smooth.

The system presented here is constructed to address all sound and not limited to musical or pitched sounds. In terms of both sound and control strategies, we aspire to universality not in the individual sound models, but in the capabilities of the machines used to create them. Manual programming of sound models is already “constrained only by our imagination”, but has practical time and effort limitations. In this paper, we are working toward the development of a data-driven system for creating arbitrary sound models. We refer to the system as a Sound Model Factory (SMF).

1.1 Previous work

Neural network and deep learning approaches in particular have been making steady progress towards automatic sound modeling. WaveNet (van den Oord et al., 2016) was a seminal contribution with its multi-level dilated convolutional autoregressive approach and extremely high-quality synthesis, and it is possible to train waveNet conditionally.

Engel et al. (2017) put WaveNet to work as an autoencoder that learns latent representations for the temporal structure of musical notes. For the 4-second musical notes comprising the NSynth database introduced in the same paper, a 125-step, 16 channel temporal embedding is learned, each vector representing a 32ms window of the note. This code sequence is then used as conditional control for a second WaveNet serving as a decoder. “Morphing” between instruments works well, but the temporal representations requires interpolating between two vectors that are themselves changing at each time step during the decoding process. The model is also capable of generating unseen note sequences and playing notes of longer duration than those it was trained on. The study was restricted to pitched musical notes, so its applicability to unpitched sounds is not known.

In many ways, GANSynth (Engel et al., 2019), also from the Google group, has held the mantle of ’state-of-the-art’ in generative musical instrument modeling since it was published. It pioneered the use of a two-channel time-frequency representation of audio training data where one channel is the familiar magnitude spectrogram, and the other is the derivative of phase which is commonly referred to as the “instantaneous frequency.” This ”IF” representation can be inverted to time domain audio using inverse Fourier transforms without the need for a process such as the iterative Griffin-Lim (1984) procedure. GANSynth produces excellent quality reconstruction on the NSynth musical instrument notes dataset.

One distinction of the GANSynth compared to the WaveNet audio encoder/decoder is that a single latent vector determines the whole temporal extent of a sound sample (e.g. a note). Furthermore, using a method developed for Conditional GANs (Mirza & Osindero, 2014), Engel et al. (2019) showed that by training conditionally, pitch can be disentangled from the timbral qualities of the sound, and then controlled during generation without having to search the latent space. For conditioning, they used a one-hot representation of pitch to augment the latent vector input.

The expressivity of GANSynth was demonstrated with a performance of Bach’s Prelude Suite No. 1[1] while morphing through dozens of different identifiable as well as novel instrument sounds over the course of the piece, however the GAN’s fixed output duration limits the resolution of the morphing to the duration of the notes.

One limitation of the IF representation, is that it works well with pitched sounds comprised of harmonic components well-separated in frequency, but struggles with unpitched sounds(Gupta et al., 2021). Noisier sounds have been addressed by others with different representations. Nistal et al. (2020) used a 2-channel real and imaginary spectrogram with a GANSynth architecture, conditioning on a set of high-level timbral descriptions (e.g. brightness roughness) each represented as floating point values, to produce convincing drum sounds. Antognini et al. (2019) used a CNN architecture inspired by the style-transfer approach using Gram matrices pioneered by Gatys et al. (2015) and developed for audio (Ulyanov & Lebedev, 2016; Huzaifah & Wyse, 2020; Grinstein et al., 2018; Antognini et al., 2019). Data are represented as magnitude spectrograms with time as the single dimension, and frequency bins as channels and are inverted with the Griffin-Lim (1984) algorithm. They also developed novel loss terms so that the style-transfer algorithm would capture rhythmic time scale patterns.

These strategies enable the generation of non-pitched sounds and textures, but are limited, like GANSynth, to generating sounds of a predetermined length (typically on the order of 1-4 seconds) given a parameter or sound as input. They are not continuously responsive to parameter changes despite continuity in the latent space. Conditioning with one-hot representations, as GANSynth does

[1] https://magenta.tensorflow.org/gansynth

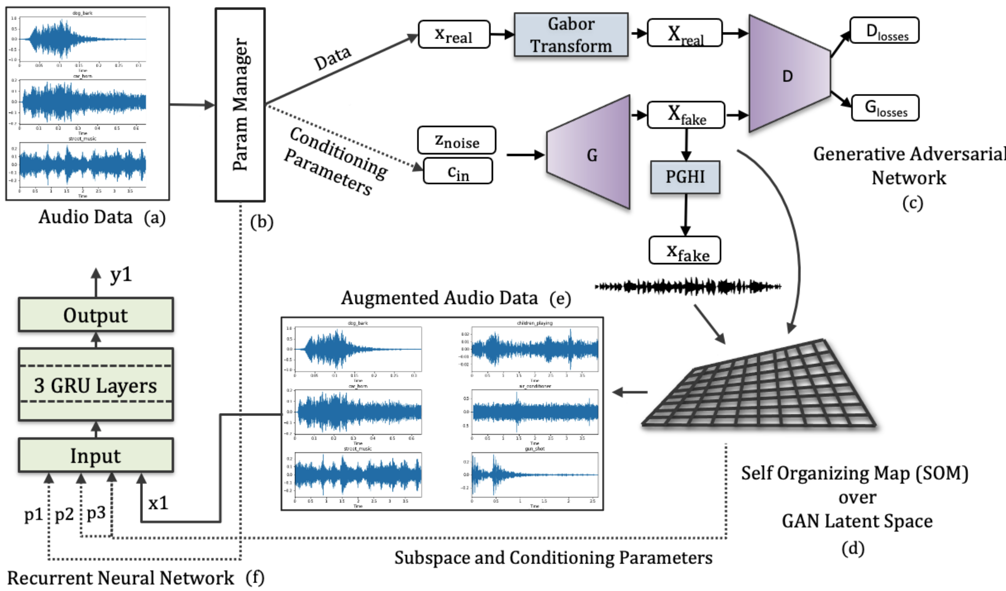


Figure 1: A schematic of the sound model factory is shown in this figure. (a) Curated datasets and optionally parameters from meta-data (b) are used to train the GAN (c). A subspace is chosen from the resulting latent space which is then adaptively adjusted using a Self-Organizing Map (d). The synthetic data (e) is sampled from the GAN and paired with the low-dimensional parameters to conditionally train the RNN (f).

for pitch, also impedes morphing in that dimension, producing between-note transitions resembling a cross fades rather than pitch glides as the one-hot vectors are interpolated.

The SMF system makes contributions extending the state-of-the-art GAN system for generative audio modeling with the capacity to produce models that can generate pitched or noisy sounds, a method for linearizing the data space of the GAN, and the ability to generate continuous audio morphing between sounds learned by the GAN with immediate parameter response times in both conditioned and unconditioned dimensions.

2 Architecture

2.1 System Overview

The SMF is comprised of multiple components with a GAN, a self organizing map (SOM), and an RNN forming the backbone of the flow as depicted in Figure 1. The model design process starts with the specification of the dataset (Fig.1a). The ParamManager (Fig.1b) represents any system for reading and writing data and metadata including parameters, any of which can be chosen to be used as conditioning extensions to the latent noise vectors provided as input for the GAN (Fig.1c).

The next step is the selection of a subspace from the high-dimensional latent space of the GAN that will define the range of sounds of the model being constructed, and the number of dimensions that the sound model will offer for parametric control. We currently select 4 points to define a 2D subspace, but the process generalizes to more dimensions. For example, having trained on the NSynth data base, one might choose two clarinet-like sounds, one at the low end of the pitch scale, the other at the top, and likewise two points for a trumpet-like sound spanning a pitch scale. A 2D mesh (Fig.1d) (of any desired resolution) with corners at the four points, defines the points in latent space that will be used to generate the sounds (Fig.1e) that, along with the two parameters used to index them, will be used to train the RNN (Fig.1f). A Self Organizing Map (described in more detail below) also smooths mesh interpolations to create more intuitive parametric control. The sound model output of the SMF is the trained RNN.

2.2 System Components

We used two datasets in the development of the SMF; one consisting of pitched sounds, the other of noisy sounds with no clear pitch.

We use a subset of the NSynth dataset (Engel et al., 2017) that consists of 300,000 single-note audios played by more than 1,000 different instruments. It contains various labels for pitch, velocity, instrument type, and more, although, for this particular work, we only make use of the pitch information as the conditional parameter. We further narrow the set to acoustic instrument types *reed* and *brass*. Like Nistal et al. (2021), we trimmed the audio samples from 4 to 1 seconds, choosing the central 1 second to remove the attack and decay transitions and any silence. We considered samples with a MIDI pitch range from 64 to 76, which finally yields a subset of approximately 6,164 audio files with 3,041 of brass type and 3,123 of reed type.

The BOReilly dataset consists of 6,583 one-second samples of synthetic textures generated by 8 different synthesizers drawn from source material used by sonic artist Brian O'Reilly[2]. The only criteria in this loosely curated collection was that the sounds be noisy and unpitched (in contrast to the NSynth set) and of stable amplitude throughout (comparable to our NSynth subset).

We use the progressively growing Wasserstein GAN architecture developed for GANSynth (Engel et al., 2019) consisting of a generator G and a discriminator D, where the input to G is a random vector z with 128 components from a spherical Gaussian distribution along with an optional one-hot conditional vector c_{in}. Training is divided into 5 stages, where the resolution of the output progressively increases at each stage by adding a new layer to the existing stack. This gradual and progressive blending in of the new layers ensures minimal perturbation effects as well as stable training of the GAN, as first proposed by Karras et al. (2017). We train separate GAN models for different datasets, each trained for 1.2M iterations, with 200k iterations in each of the first three stages on batches of 12, and 300k in the last two stages on batches of 8, that requires upto 1.5 days on an NVIDIA Tesla V100-SXM2-32GB. The Wasserstein GAN minimizes an approximation of the Earth Mover (EM) distance, that has been shown to manage issues with previous GANs such as mode collapse (Arjovsky & Bottou, 2017; Arjovsky et al., 2017). The discriminator D estimates the Wasserstein distance between the real and the generated distributions.

Similar to Engel et al. (2019), for the NSynth dataset, we sometimes train conditionally on pitch with the goal of achieving independent control of pitch and timbre. To do that, a one-hot representation of musical pitch is appended to the latent vector. Unconditional GAN training (no learning of control parameters) was used for the BOReilly dataset or when combining the BOReilly and NSynth datasets.

For audio data representation, rather than the 2-channel IF used for GANSynth, we use a single channel, 2-dimensional log magnitude spectrum and the Phase Gradient Heap Integration (PGHI) method (Průša et al., 2017) for a non-iterative method to reconstruct the time signal. Marafioti et al. (2019) found that the PGHI algorithm worked well on synthetic spectra produced by GANs. Gupta et al. (2021) showed that training the GANSynth architecture using the PGHI representation and inversion produces results equivalent to the IF representation for pitched sounds, and significantly better audio quality for wideband, non-pitched or fast changing signals such as pops, and chirps. Time-frequency representations of 16kHz sampled audio are computed using an FFT size of 512 with a hop size of 128 samples (i.e. 75% overlap between consecutive frames).

The RNN[3] used in the SMF is comprised of 3 GRU layers with 256 hidden nodes each. A fully connected embedding layer takes the floating point audio and conditioning parameters to the GRU layer input. A softmax layer at the output produces a probability distribution across 256 values interpreted as mu-law encoded audio sample values predicting the next sample in time. RNNs are trained on the sound samples generated by the GAN latents sampled on a 21x21 grid, and conditioned on the parameters that index the grid. Training for this stage on an NVIDIA 3090 on 256 sample sequences in batches of 128 for 100K iterations requires approximately 3 days.

[2]https://vimeo.com/dendriform

[3]https://github.com/[anonymized]

3 Connecting the GAN and the RNN

The size of the GAN latent space (in our case, a fairly typical 128 dimensions) is too large to serve as a parametric interface for effective human control of musical performance. This motivates the dimension reduction accomplished by choosing points that define a subspace. This task seems daunting since a 128 dimensional space is large. There are various ways of "inverting" a GAN to find parameters corresponding to specific data space examples (Xia et al., 2021). However, in practice we have found that generating a hundred or two random vectors does a reasonable job at generating sounds similar to much of the real data used for training. The designer's choice of these sounds is critical, as it circumscribes the range of sounds the final synthesis model will be able to generate, as well how they will be parametrically navigated.

After the choice of latent vectors/sounds is made, the resulting space is sampled with a mesh pattern, and the GAN is used to generate sounds for all points on the mesh. Then the pairing of the now 2D parameter vector and the resulting sound at each point can be used to train the RNN. Original and adapted grids generated in this way are available for auditioning online for the Trumpinet and BOReilly sets[4].

3.1 Parameter Linearization

GANs model the structure of the data space using an explicit distribution of latent vectors that allow the learned probability density function to be sampled. The space tends to be smooth in that nearby points in latent space yield nearby points in the output audio data space(Goodfellow, 2016; Mao et al., 2019; Jahanian et al., 2019) giving rise to the GAN's remarkable ability to interpolate, or "morph" between data points. However, there is no guarantee that the perceptual space is linear with respect to the latent space. That is, a given delta in the latent parameter values can cause very different changes in the perception of the sound depending on the location in latent space. In practice, we have found that for latent values that correspond to sounds similar to those in the real dataset, parameter changes tend to have relatively small effects, where as at some points in the latent space between regions of real-data like sounds, there is a kind of boundary where small parameter changes result in large perceptual changes.

To address the issue of consistent interpolation which is central to sound model design, we introduce a Self Organizing Map (SOM) (Kohonen, 2012) that sits in the SMF system between the learned space of the GAN and the training of the RNN. The latent vectors function as the SOM "weights" associated with each point on a 2D mesh, and the reduction of a measure of the perceptual difference between sound generated by neighboring latent vectors on the grid serves as the function driving the adaptation so that differences between sounds generated by neighboring mesh points become perceptually more uniformly distributed. The mesh point update equation is

$$g_{i,j} \mathrel{+}= \delta \sum_{m,n \in N} g_{m,n} \left(\sum_{p,q} |S^{i,j}_{p,q} - S^{m,n}_{p,q}|^2 \right)^{\frac{1}{2}} \tag{1}$$

where N is the 8-node neighborhood (horizontal, vertical, and diagonal) of $g_{i,j}$, δ is the step size, $S^{i,j}$ is the spectrogram generated by the GAN by the latent vector associated with mesh node i, j, and p, q indexes the time and frequency points of the spectrograms. The corners of the grid are always "pinned" to the initial latent vector chosen to define the sub-manifold, and for some experiments, we restrict movement of mesh points lying on the lines connecting corners to remain on those lines.

The adaptation of the latent vectors on the mesh is driven by the L2 distance between the 2D spectrogram images as a proxy for perceptual difference. Although audio perceptual distance is notoriously difficulty to quantify in general, sound corresponding to neighboring latent vectors are already organized by spectral proximity. We find that linearizing distances locally in this way yields significant improvements to the overall perceptual smoothness of the parameter space, and we validate this claim with user studies reported below.

We can visualize the mesh adaptation using the 2D grid space (Fig ure 2). The contour plot represents the average difference in the spectrograms produced by one grid point and its eight neighbors.

[4] https://animatedsound.com/iclr2022/#grids

The effect of the adaptation can be visualized by stretching the grid points back to their nominal index value locations which stretches the underlying space with it. In Figure 2, the linearization of the perceptual space is seen in the regularization of the distance between contour lines on the contour plot and the reduction of the maximum difference.

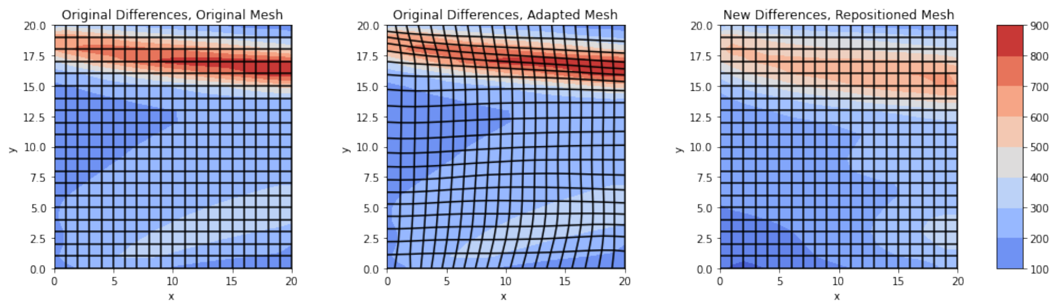


Figure 2: The SOM adapting to reduce differences between mesh neighbors of the function value. The upper two mesh corners correspond to a clarinet and a trumpet sound playing the same pitch. The bottom two corners are complex BOReilly textures. A border-like structure of sudden change divides the two regions. The contour plot shows average spectrogram differences with it 8 neighbors at each grid location. (a) Initial mesh (b) adapted mesh (with edges pinned) over the original differences contour (c) the smoothed differences at their new mesh positions.

4 Evaluation

As a system, we want to evaluate the capabilities compared to others that address the same or similar goals - the production of sound models that have miminal PRTs, can generate non-repetitive sounds for arbitrary lengths of time, and that can interpolate smoothly between parameter values. We also want to understand the kinds and quality of sound the models created by the system are capable of generating, particularly in terms of complexity.

4.1 Human Evaluation adaptively smoothed latent space

Our listening tests were designed to test for perceptual linearity between two points in the GAN's latent space by asking participants to listen to two sound clips, one sampled from the adapted mesh space (pinned corners or pinned corners with constrained edges) and another sampled without this adaptation. The sound clips were created by first selecting two points in the GAN latent space, selecting 20 equidistant samples between those points and joining those samples to create one clip. The space between those two points was then adapted using our SOM technique and sampled again to create a second clip. These two clips formed one pair in a comparison trial with each sound lasting for 13-15 seconds. The mesh adaptation for the BOReilly sounds used pinned corners whereas for NSynth sounds used pinned corners with constrained edges. Our listening experiments were conducted on Amazon's Mechanical Turk (AMT) with user consent, are anonymized, and were approved by our university department's ethics review committee.

We recruited 40 participants on AMT and given that these participants may not be audio or sound experts, our experiment design used simple language and pairs of icons (see Table 1) to convey our intent and to gather meaningful responses from the test. The participants were required to listen to both sounds before answering the questions. No submissions from participants were rejected during these experiments. The participants were paid $0.10 per task which took less than 90 seconds on average.

We identified two types of non-linearity in sound interpolations. One type is when the interpolation takes a "detour" (e.g. passing through a flute sound during a transition from a clarinet to a trumpet, or passing through a pitch not between the pitch of the endpoint sounds) and another type when step sizes in the interpolation parameter results in the perception of irregular size steps in the quality of the sound. To probe for directness in transitions of sounds from one end point to the other, we asked participants to associate a "direct" icon or a "detour" icon with each pair of sounds. To test for irregular step sizes in the sampled GAN data space, the participants did the same with an "Even Steps" icon and a "Uneven Steps" icon. The mutually exclusive association of each pair of ions with the sounds could be made with one mouse click and drag [5]. Responses from 520 comparison trials for NSynth sounds and 840 comparison trials for BOReilly sounds were collected. The trials were loaded in a random sequence to AMT and its results are tabulated in Table 1.

	Sound samples	NSynth	BOReilly
Direct vs.	Mesh adapted	**57.50%**	**61.07%**
Detour	GAN Only	42.50%	38.92%
Even steps vs.	Mesh adapted	**59.42%**	**60.47%**
Uneven Steps	GAN only	40.58%	39.52%

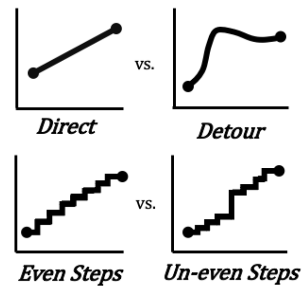


Table 1: Human evaluation or listening test results and visual correlates and icons developed for Mechanical Turk participants to visually associates perceptual differences in the sounds in a comparison trial are shown. Icons (right) capture linearity in perception of the sound's transition from its starting point towards its end (Direct vs. Detour) as well as the perceptual measure of even or uneven jumps the sound's makes from its starting point towards its end (Even vs. Uneven steps).

4.2 Parameter Response Time

In this section, we demonstrate the ability of the SMF system to generate sound models that meet the playability requirements identified in the beginning of this paper. The RNN was trained using only steady-state pitch parameters, but parameters are manipulate during generation. Figure 3a shows a one-octave stepped arpeggio followed by a descending one-octave glide. We measure the PRT manually by verifying whether the wave period at a particular instance corresponds to the intended pitch at that instant. We find that the parameter response is immediate for both steps and glides as shown in Figure 3.

4.3 Sound Quality Evaluation based on Audio Classification

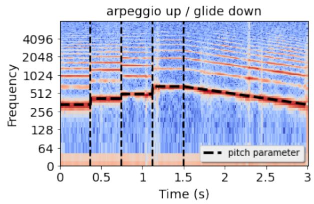
In this section, we try to quantitatively validate that the quality of a GAN generated audio is similar to that of our proposed SMF generated audio texture for the same parameter settings. Since GAN generated audio have been shown to be of high perceptual quality (Engel et al. (2019); Nistal et al. (2021)), similarity of the generated audio from our proposed architecture to that of GAN would imply similarity in their perceptual quality.

Since the latent space of GAN consists of timbre of the two instrument classes as well as the timbres in-between the two classes, a class label cannot be assigned to every point in this latent space, as the in-between timbres cannot be labelled with a class. Therefore, the standard method of inception score computation (Salimans et al. (2016)) will not be applicable in this case.

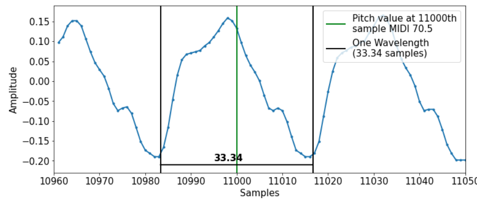
For quantitative validation, we train an audio classification network (Palanisamy et al. (2020)) with the brass and reed instrument classes from NSynth dataset. This subset has 56-76 MIDI pitch values with velocity 127, with a total of 2,225 audio files, split into 80% training and 20% validation. The audio classification network consists of a ResNet model initialized with ImageNet pretrained weights. This scheme of training has achieved state-of-the-art audio classification performance when fine-tuned with standard audio classification datasets, as shown by Palanisamy et al. (2020). We trained this network to classify the two instrument classes by fine-tuning it on our Nsynth subset data. The validation accuracy of this model is 100%.

In this experiment, we were interested in observing whether a set of audio files generated from a latent space of the GAN have the same distribution of logit values (values at the output layer before

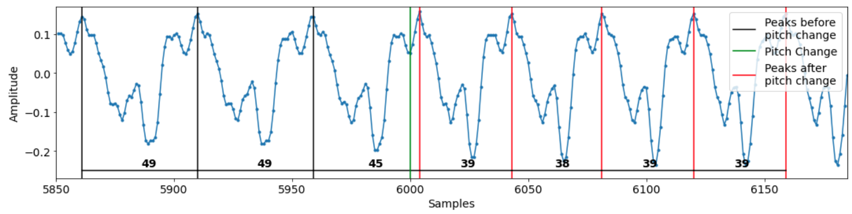
[5]https://animatedsound.com/iclr2022/ui/amt-instructions-template.html



(a) Arpeggio and glide



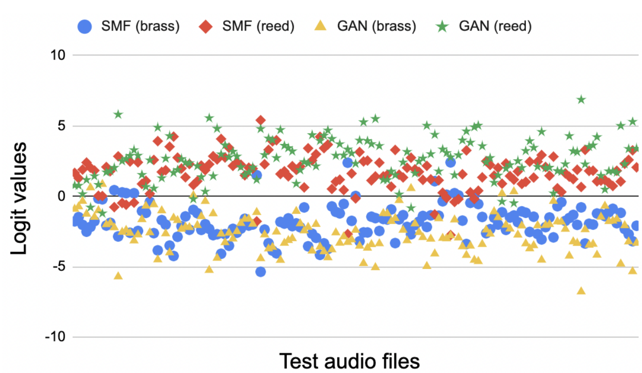
(b) Wave period during pitch glide



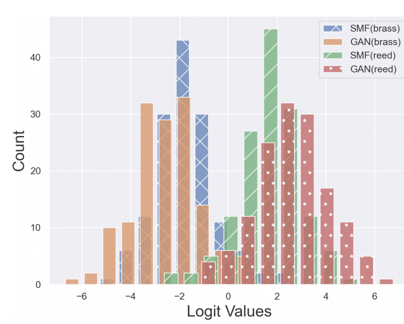
(c) Wave period at pitch step change

Figure 3: (a) Parameter changes and spectrogram of RNN output for (a) an arpeggio over an octave (midi number 64, 68, 71, 76) followed by a one octave glide. The PRT is more precisely quantified in (b) for a descending one-octave glide (MIDI note 76-64), the period of the waveform centered at the 11000 sample mark matches the gliding pitch parameter of MIDI note 70.5 (34.35 sample wavelength) exactly at that point, and (c) for pitch step where we identify peaks before and after the pitch change (green line) to show that the wave period changes immediately after the pitch steps from MIDI 64 (48.56 sample wavelength) to 68 (38.53 sample wavelength).

the class labels are assigned) in the audio classifier, as the set of audio files generated from the proposed SMF (i.e. GAN+RNN) system for the same parameter settings. Parameter settings, in this case, means the pitch and timbre indices from the GAN-generated latent space. We used 143 such pairs of audio files. The two logit values corresponding to the two audio classes (brass and reed) for each of these files, i.e. (SMF(brass),SMF(reed)) and (GAN(brass),GAN(reed)), are presented in Figure 4a. The histogram of these logit values are shown in Figure 4b. Qualitatively, we observe the distribution of logit 0 values of GAN and SMF audio files are similar, and the distribution of logit 1 values of the two types of audio files are similar. Moreover, 127 out of 143 pairs of audio files get classified into the same instrument class, i.e. 88.8% of the test pairs are classified into the same class. This analysis shows that the audio generated from the proposed SMF architecture are similar to that generated from the GAN.



(a)

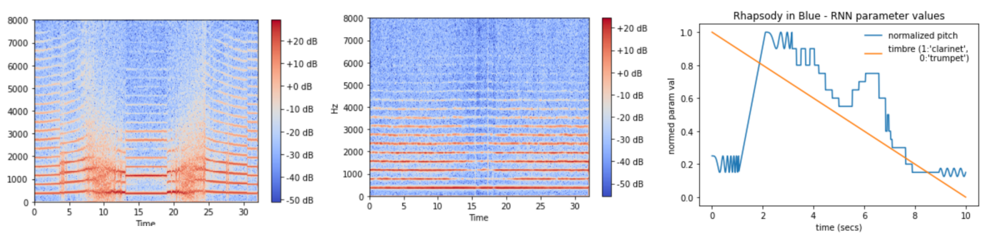


(b)

Figure 4: Logit values from the penultimate output layer of the audio classifier for the two sets of 143 test audio files, one set from the GAN, and the other from the proposed SMF model (GAN+RNN). The two logit values are depicted as *(brass) and *(reed). (a) The raw logit values for all test audio files, and (b) the histogram of the logit values.

4.4 CONTINUOUS INTERPOLATION OF PITCH AND TIMBRE

GANs are structurally unable to continuously interpolate parameters for audio because time is dimension of the data representation. One-hot representations such as used for pitch in GANSynth produce audible artifacts at ”in between” values. Wyse (2018) showed that an RNN can interpolate between widely spaced conditioned pitch values. However, we found the RNN less capable of interpolating between timbres as can be seen in Fig. 5a. The GAN, however, can synthesize convincing timbres perceptually between training examples. When synthetic GAN data are used to train the RNN, the result is the best of both worlds - convincing in-between timbres that can be smoothly and continuously interpolated (Fig. 5b). A musical example illustrates the combined capabilities with fast and slow pitch changes including vibrato and a continuous morph between clarinet and trumpet over a rendering of of the opening segment of George Gershwin’s Rhapsody in Blue (Fig. 5c).



(a) (b) (c)

Figure 5: Spectrograms of a steady-pitch trumpet-clarinet-trumpet glide with an RNN (a) trained at endpoints only, (b) trained with intermediate synthetic data from GAN. (c) Parameter sequence for a “reinterpreted” opening segment of George Gershwin’s Rhapsody in Blue with glides, various note lengths, vibrato, and a continuous clarinet-to-trumpet instrument morph (audition online[6]).

5 CONCLUSION

A few noteworthy limitations are left for future work. For example, by selecting a subspace of the GAN latent space, the SMF makes a trade-off between low dimensional control over a constrained sound space of the RNN and the hundreds of parameters and diversity of the GAN sound space. More control over that balance would benefit sound model design.

The linearization of the perceptual sound space with respect to parameters needs further exploration. Although the SOM (1) improved the perceived smoothness of transitions, they are still neither perceptually or objectively uniform. The neighborhood used to compute updates to the grid could be expanded, or paths between the anchor points could even depart from the 2D manifold in a search for smoother transitions.

Although the PGHI representation and inversion provides high quality resynthesis of non-pitched sounds, the current SMF is limited in the complexity of the temporal structure of audio textures it can capture. For example, previous synthesis models capable of learning to generate randomly spaced clicks conditioned on rate have needed lots of data to capture the temporal variability at any given rate parameter. However, GANs generate one fixed length sample for any given latent parameter vector. If the GAN is to provide the necessary variety of sound patterns for training a downstream model with this kind of complexity, we would have to identify a whole region of the GAN latent space to map to a single parameter value for training the RNN, not just a single point.

The innovations introduced at the system level for the SMF come from a) the use of the single channel and PGHI representation and reconstruction with the GANSynth architecture, b) the linearization of a slice of the latent space of the GAN using SOMs, and (c) the exploitation of the GAN parameter/sound pairing to train an RNN. The SMF contributes novel audio capabilities by combining immediate parameter response times, smooth interpolation capabilities of the GAN’s conditioned and unconditioned parameters, “infinite” duration sound synthesis, and the ability to generate a wider variety of audio timbres more complex than pitched instrument sounds.

[6] Audition at https://animatedsound.com/iclr2022/#pitch-timbre

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