STYLE-BASED DRUM SYNTHESIS WITH GAN INVERSION

Jake Drysdale
jake.drysdale@bcu.ac.uk
SoMA Group

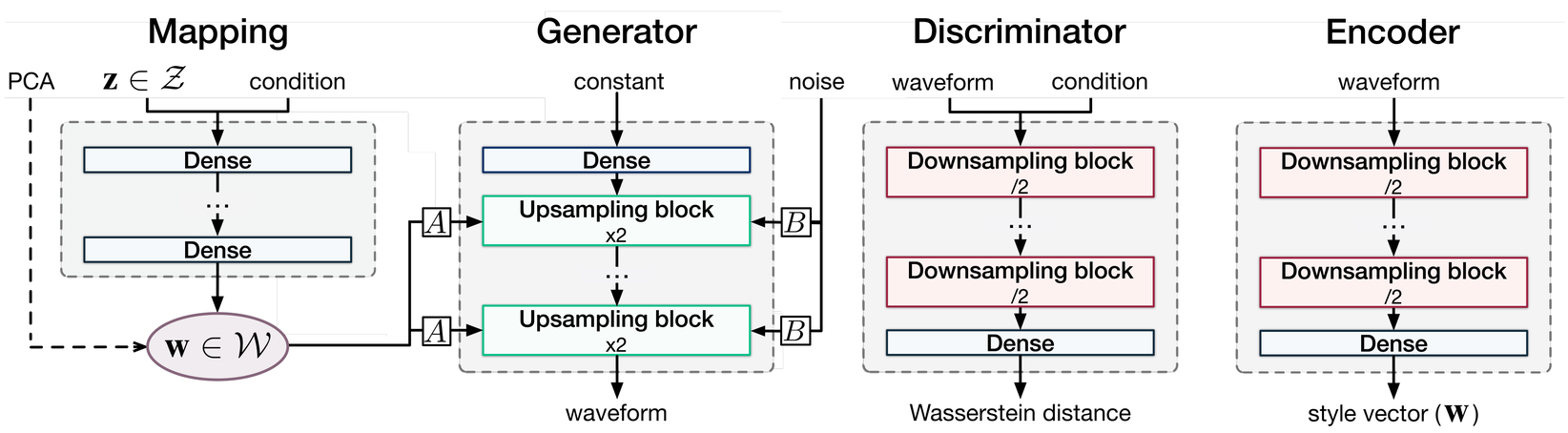
Maciej Tomczak
maciej.tomczak@bcu.ac.uk
DMT Lab

Jason Hockman
jason.hockman@bcu.ac.uk
Birmingham City University

INTRODUCTION

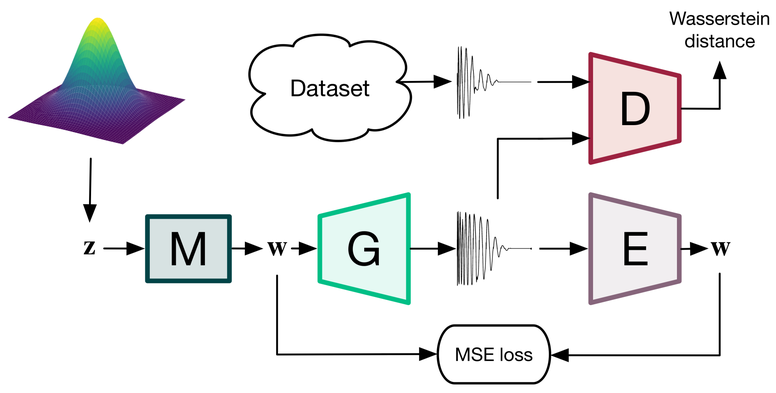
- Generation and transformation of drum sounds using style-based generative adversarial network
- Functional control over synthesis, based on principal component analysis applied to intermediate latent space
- Enables conditional generation of kick drum, snare drum and cymbals
- Operates directly on waveforms
- Synthesis can be controlled by input audio through use of an audio inversion network

SYSTEM OVERVIEW



TRAINING PROCEDURE

- 200k iterations
- Adam optimiser
- Learning rate = 2e-3
- Batch-size = 64
- Wasserstein loss
- Gradient penalty



DATASET

- One-shot drum sounds
- Kick, snare and cymbal labels
- 16-bit, 44.1kHz WAV
- 16384 sample length
- Pitch augmentation (± 3 semitones) applied to increase size of dataset

GAN ARCHITECTURE

Architecture is based on [1], and is extended with conditional style-based generator network [2].

Mapping network (M):

- Conditional multi-layer perceptron
- Transforms latent space Z into an intermediate latent space W
- Learns to create disentangled features that are used to control G

Generator network (G):

- Generates waveforms
- Series of upsampling and convolutional layers
- Intermediate latent vectors w integrated at each upsampling block through adaptive instance normalisation (AdaIN)
- Inconsequential noise injected into each block to model stochastic variation

Discriminator Network (D):

- Estimates Wasserstein distance between generated and real drum sounds

Encoder Network (E):

- Replicates D
- Output units match dimensionality of latent space

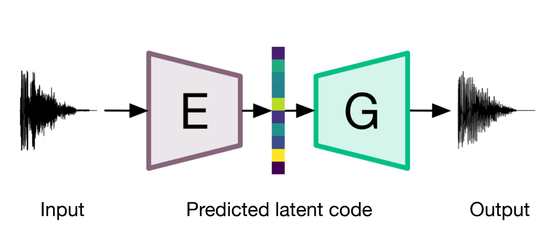
AUDIO INVERSION

Encoder:

- E trained to embed a given waveform into intermediate latent space of a pre-trained GAN
- Predicted latent vectors fed into the G to synthesise drum sounds with similar characteristics to input waveform

Training:

- Dataset created by generating 10000 drums with pre-trained G
- Miinimise mean square error between ground truth latent vectors and predicted latent vectors



PCA FOR USER CONTROL

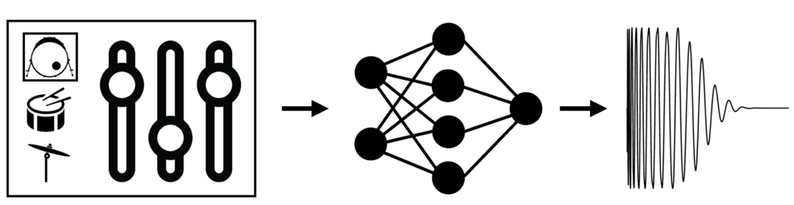
- Following [3], principal axes of W are identified with PCA to obtain coordinates that emphasise variation
- G feature controls are achieved by layer-wise perturbation along principal directions
- Coordinations are scaled with control parameter that can be modified by user

SYNTHESIS PARAMETERS

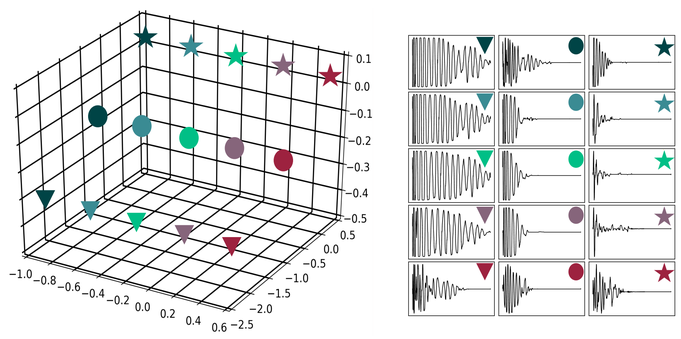
Style-based drum synthesis with GAN inversion allows user to interact with system parameters in 3 ways:

- Sampling from intermediate latent space and exploring timbral characteristics with preset number of controls
- User can input single drum sample to encoder network and modify its characteristics with style faders
- Encoder can be used to reconstruct 2 arbitrary drum sounds, and various interpolation techniques may be incorporated for style transformation

High-frequency content of generated drum sounds can be shaped by introducing Gaussian noise into individual layers of pre-trained G.



WAVEFORM INTERPOLATION



Interpolation in latent space for drum generation. Drums are generated for each point along linear paths through latent space (left). Gennerations appear across rows (right).

DEMO

- Open-source code
- Audio examples
- Python demo

https://jake-drysdale.github.io/blog/stylegan-drumsynth/

[1] Drysdale, J., Tomczak, M. and Hockman, J., "Adversarial synthesis of drum sounds," *DAFx,* 2020.

[2] Karras, T., Laine, S. and Aila, T., "A style-based generator architecture for generative adversarial networks," *CVF Conference on Computer Vision and Pattern Recognition*, 2019.

[3] Härkönen, E., Hertzmann, A., Lehtinen, J. and Paris, S., "GANspace: Discovering interpretable GAN controls," *NIPS*, 2020.

DMT Lab
DMTLAB.BCU.AC.UK

BIRMINGHAM CITY University