M2C: Concise Music Representation for 3D Dance Generation (Supplementary Material)

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1. Motion GPT and SM-GPT

We utilize the official implementation for our baseline method, Motion GPT [1]. We are using this implementation as the basis for our proposed modification, the SM-GPT. For our ablation study (see Table 3), we present the result obtained by retraining Motion GPT network using their original configurations.

2. Ablating Number of K

We first experiment by reducing the codebook and setting $K = 512$ to compensate for the lack of code variations when using two codebook (refer to Table 1). We perform a total of two experiments, one utilizing the same network structure as the dual codebook approach (using $D_1(x)$), while the other utilizes $D_2(x)$ with a slight modification at the decoder to use Conv1D instead of ConvTranspose1D. We found that the former performs better compared to the latter across all metrics, which indicates that the $D_2(x)$ is less ideal for the music decoder.

Afterwards, we experiment with the dual codebook design by changing the number of K for both codebooks. To accomplish this, we add an FC layer to both $E(x)$ and $D(x)$ to adjust the dimension of the latent variable. This adjustment is necessary due to the downsampling effect, which results in a default latent variable dimension of 55 (8 times downsampling from 438-dim music features), which we utilize as the baseline value for K. The results from Table 1 indicate that this approach is less ideal than directly using the encoded 55-dim feature.

3. Codebook Analysis

We plotted the frequency distribution using three different values of K: 32, 55, and 64 (as shown in Figure 1, Figure 2, and Figure 3, respectively). We observe that setting K as 55 or 32 encourages the network to fully utilize every key in the codebook, as there are less keys available to represent the data. However, we also notice that using $K = 32$ does not highlight the difference of each key as clearly as the other K settings, as every key is utilized by multiple combinations of genre. This is not evident in the $K = 55$ or $K = 64$ setting, as some keys are used exclusively by specific genres.

Method Name	Accuracy ↓		Diversity ↑	
	FID_k	FID_g	DIV_k	DIV_g
GT (AIST++)	17.10	10.60	8.19	7.45
Single Codebook, $D_1(x)$	22.10	10.21	8.63	5.71
Single Codebook, $D_2(x)$	36.17	16.02	5.82	4.20
Dual Codebook, K = 32	20.86	8.84	6.61	6.02
Dual Codebook, K = 48	24.43	10.58	7.23	5.54
Dual Codebook, K = 64	26.60	10.03	5.93	5.50
M2C +SM-GPT +*new norm*	18.09	8.62	6.80	5.82

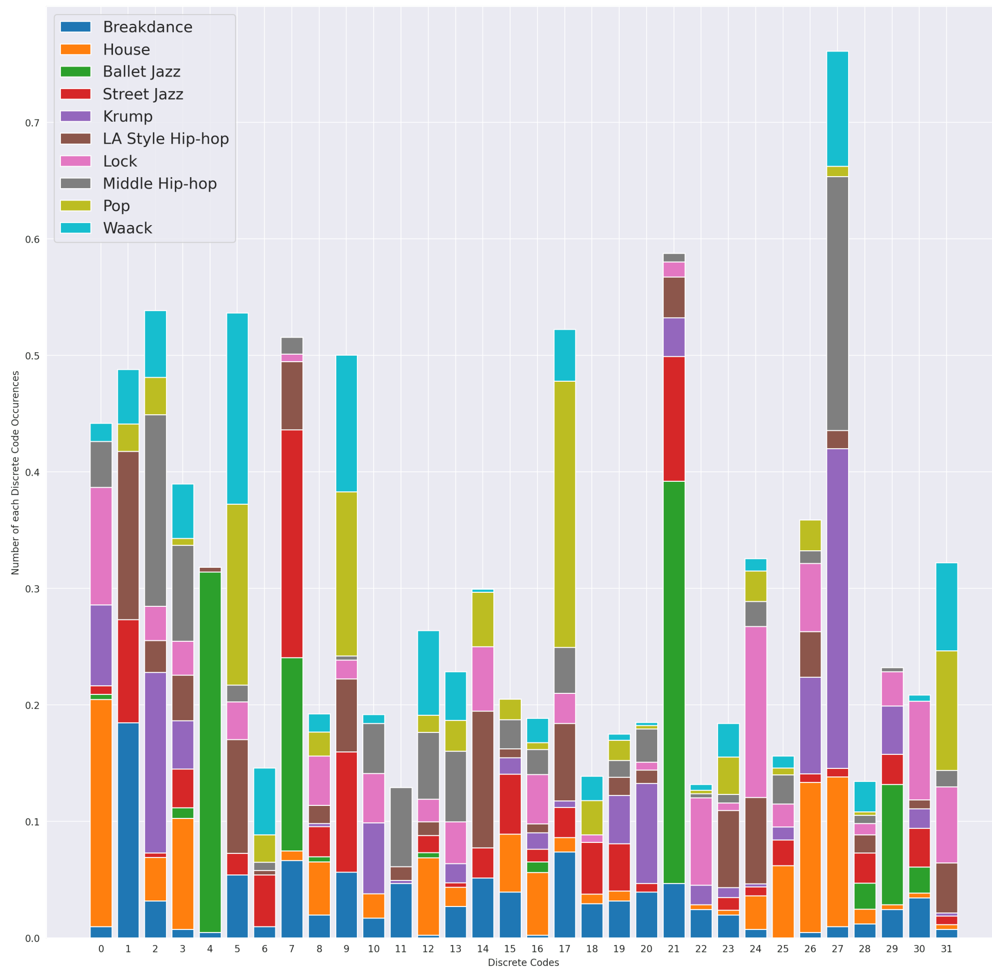
Table 1: **M2C network codebook ablation study**. The best and second best results are presented in **bold** and underline, respectively. We apply *new norm* during each of these training process.

4. Qualitative Result

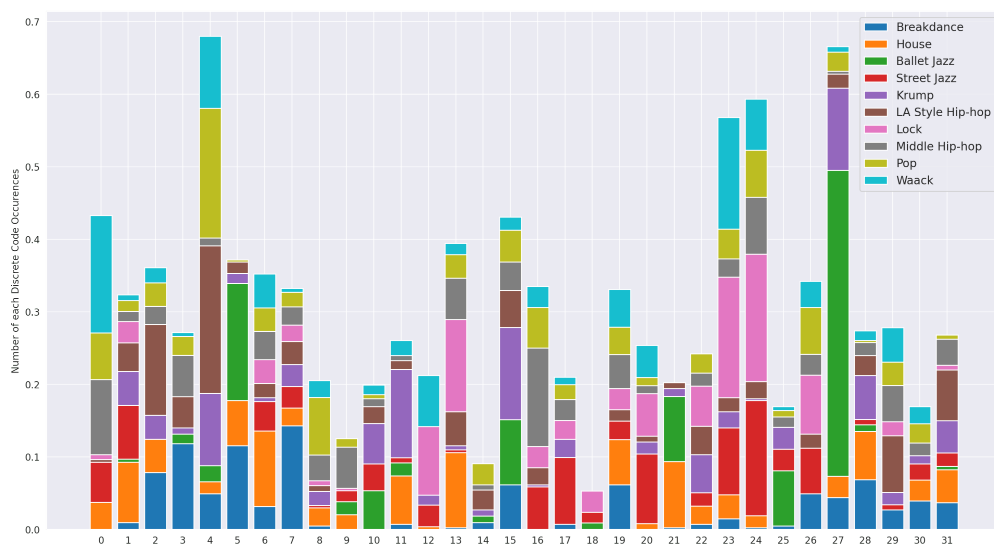
Figure 4 some generated dance motion from our proposed method. We present a total of 6 sample of generated dance motions, each belonging to a different dance genre.

References

[1] Li Siyao, Weijiang Yu, Tianpei Gu, Chunze Lin, Quan Wang, Chen Qian, Chen Change Loy, and Ziwei Liu. Bailando: 3D dance generation by actor-critic GPT with choreographic memory. In *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11040–11049, 2022. 1

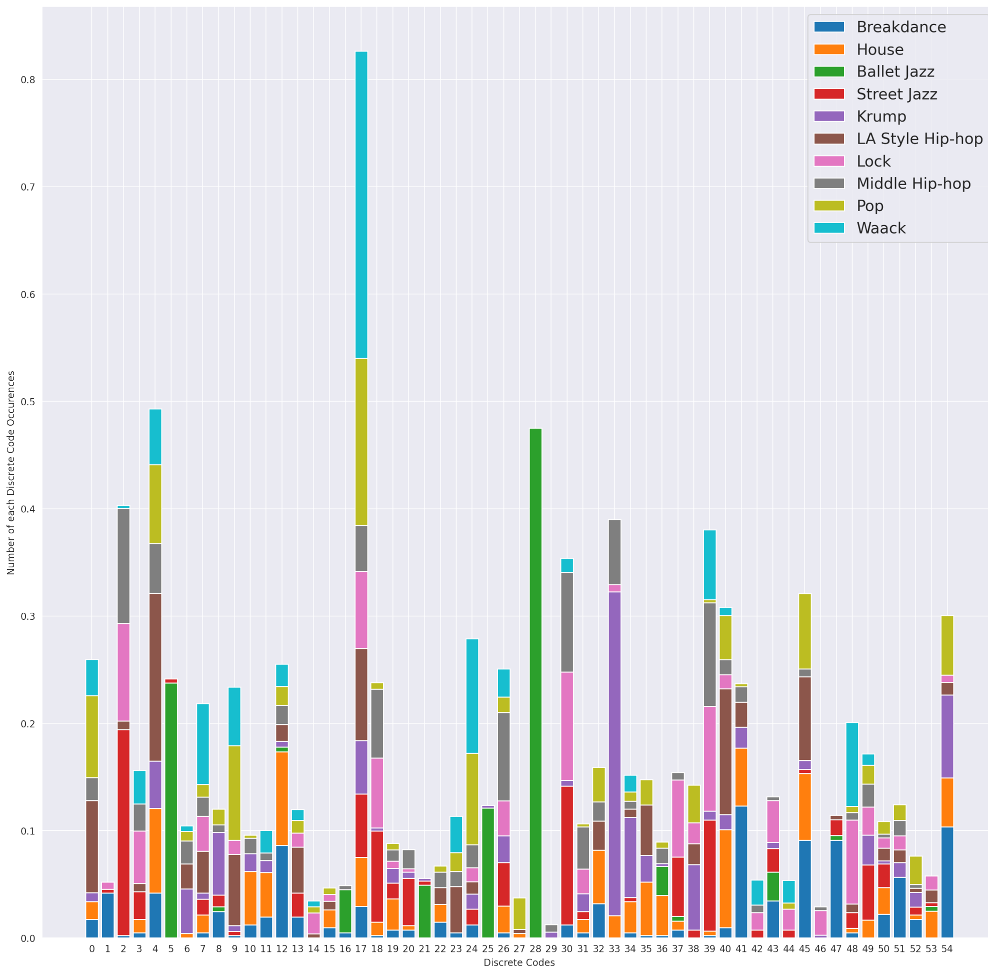


(a) M2C C_1 music code frequency distribution.

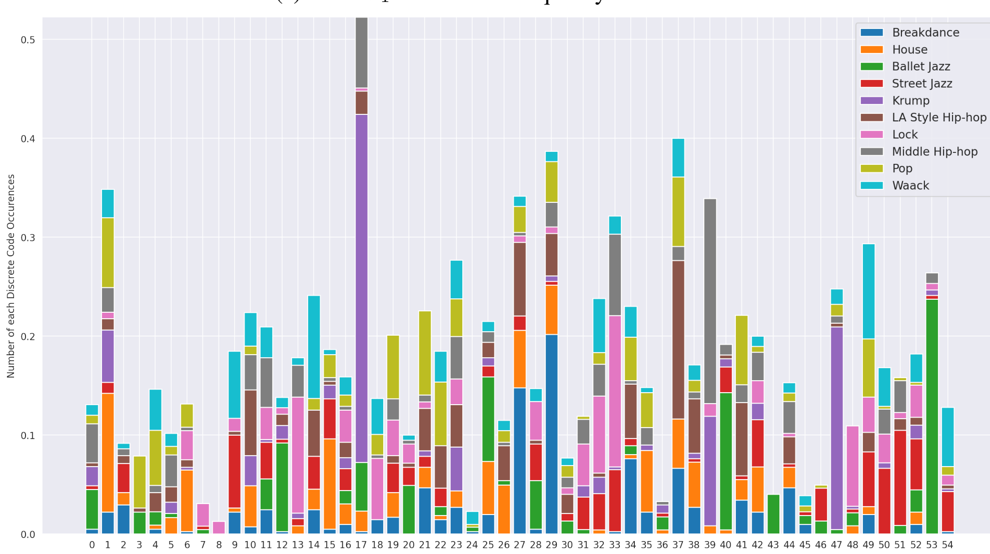


(b) M2C's C_2 music code frequency distribution.

Figure 1: **M2C's music code distribution within each codebook** ($K = 32$)**.**

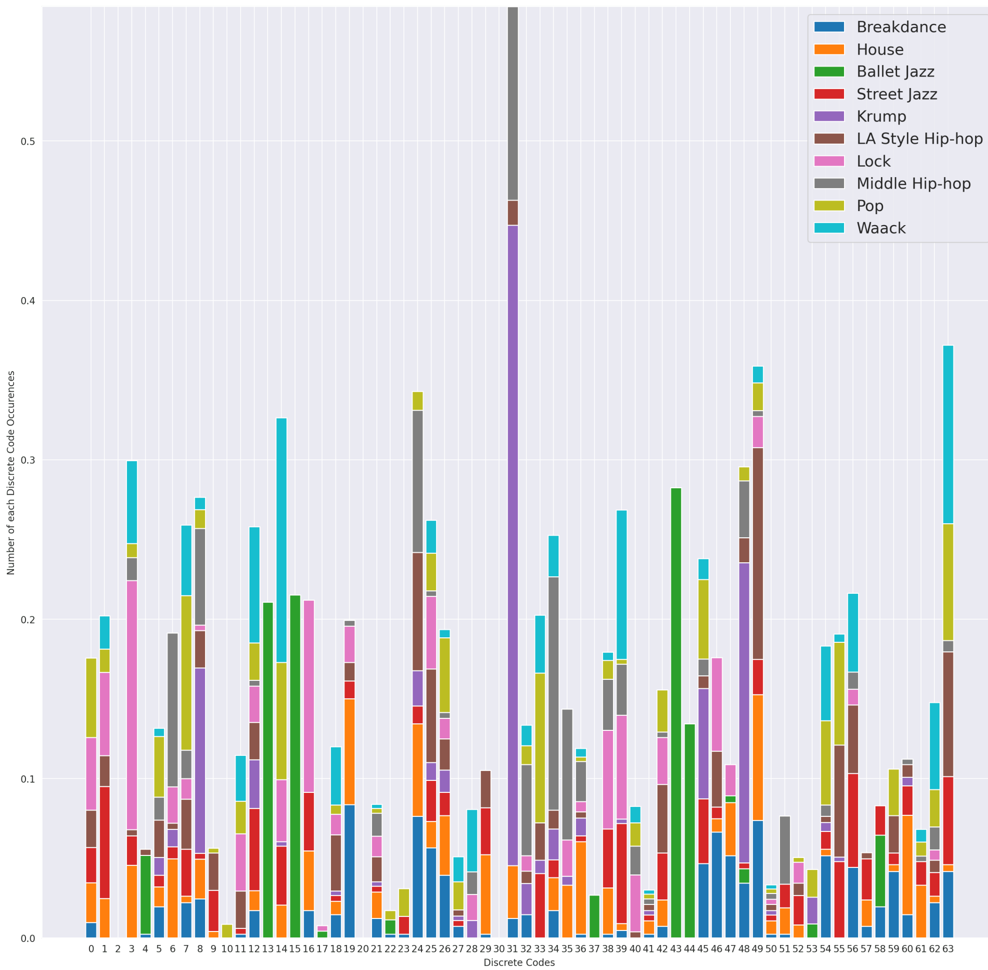


(a) M2C C_1 music code frequency distribution.

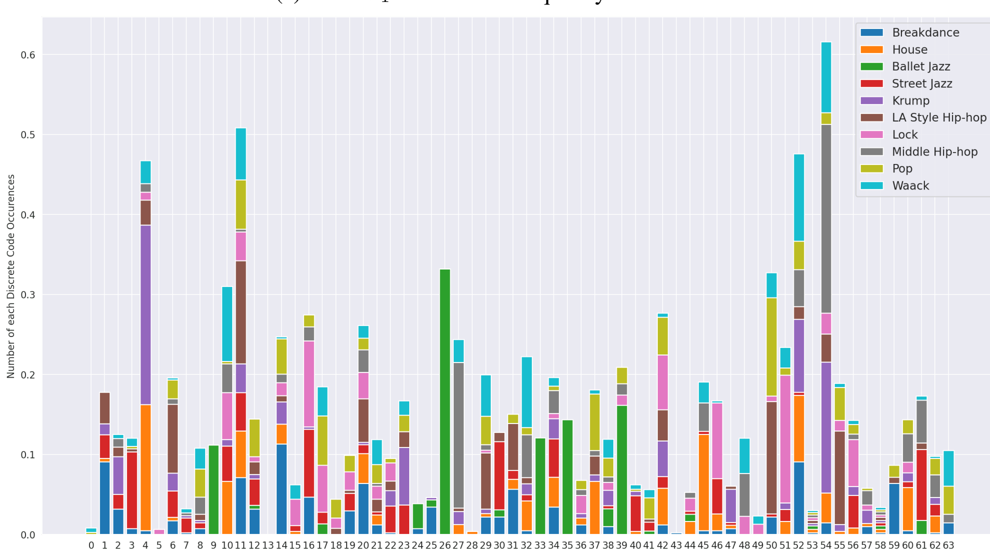


(b) M2C's C_2 music code frequency distribution.

Figure 2: **M2C's music code distribution within each codebook** ($K = 55$**).**

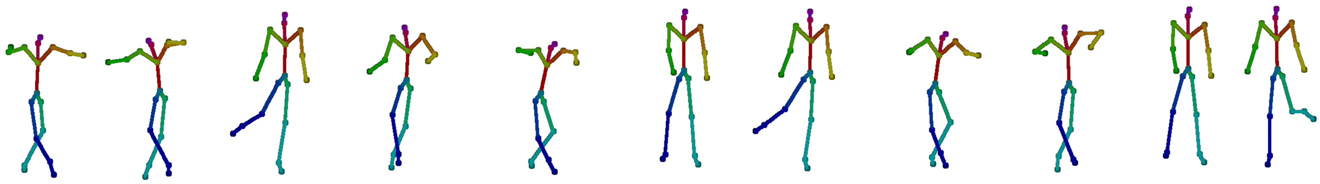


(a) M2C C_1 music code frequency distribution.



(b) M2C's C_2 music code frequency distribution.

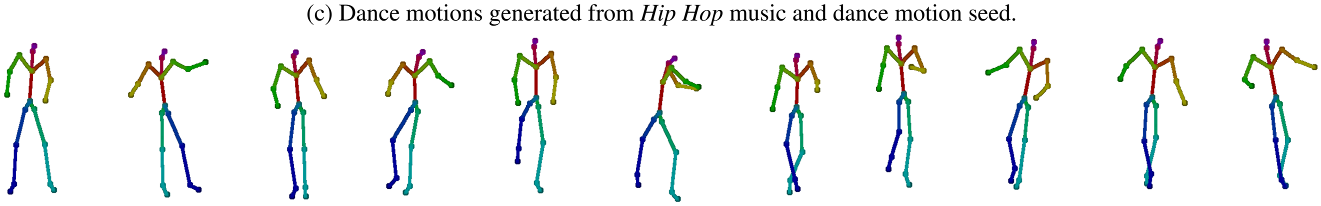
Figure 3: **M2C's music code distribution within each codebook** ($K = 64$**).**



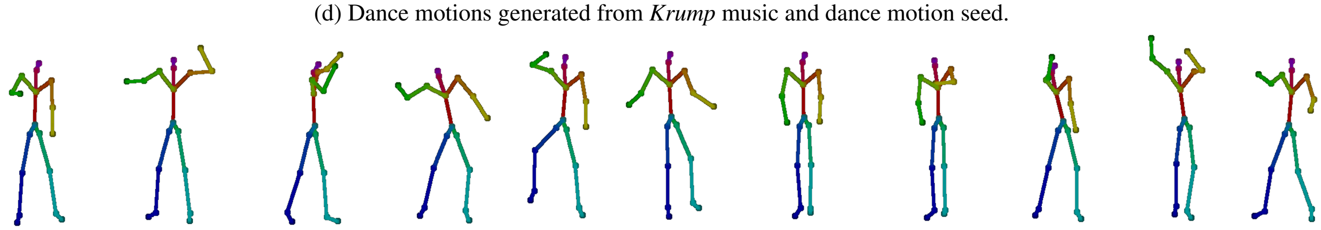
(a) Dance motions generated from *Breakdance* music and dance motion seed.

(b) Dance motions generated from *Ballet Jazz* music and dance motion seed.

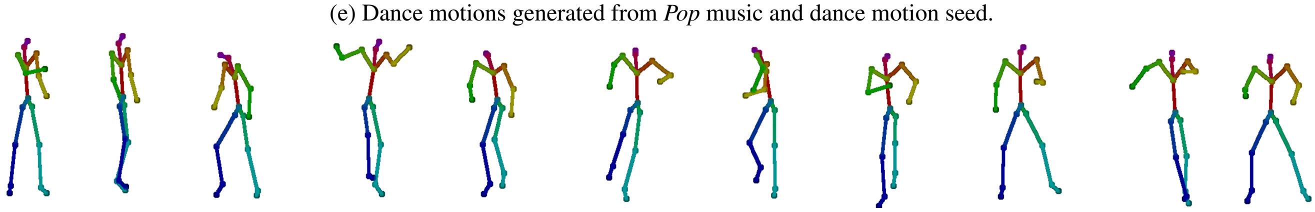
(c) Dance motions generated from *Hip Hop* music and dance motion seed.



(d) Dance motions generated from *Krump* music and dance motion seed.



(e) Dance motions generated from *Pop* music and dance motion seed.



(f) Dance motions generated from *Waack* music and dance motion seed.

Figure 4: **Generated dance motions using our proposed method.**