Characteristics Study of Dance-charts on Rhythm-based Video Games

Yudai Tsujino, Ryosuke Yamanishi and Yoichi Yamashita
College of Information Science and Engineering
Ritsumeikan University
Kusatsu, Japan
{is0221rs@ed, ryama@fc, yyama@is}.ritsumei.ac.jp

***Abstract*—This paper studies the characteristics of dance-charts on rhythm-based video games while clustering the dance-charts with the track features. In the opinion of expert players, it is considered that the difficulty level of the rhythm-based games depends on multiple features for the song and chart. The difficulty levels for dance games has not well been studied though it has been already done for other genres of games. This paper designed the track features for dance games, which would be varied depending on characteristics of the track. Moreover, we conducted a dance-charts clustering by using the k-means method with the designed features. As a result of the clustering, it was confirmed that the clusters were composed mostly based on the step frequency and the complexity of rhythm. Also, it was found that the scores with the extremely characteristic features were separated from other scores and clustered as one class with themselves. The discussion in this paper indicated a possibility for the objective evaluation of the dance-charts.**

***Index Terms*—Rhythm-based games, the study of the difficulty levels, clustering game charts.**

I. Introduction

Dance is no longer just a musical expression but also games present days. Dance games, such as *Dance Dance Revolution*, are typical and popular rhythm-based video games. In most of the rhythm-based video games, players perform some actions corresponding to the displayed chart. There are varied types of players, beginners to experts, so multiple charts corresponding to each difficulty level are prepared for each song.

For entertaining varied and many players, the difficulty should be considered carefully [1]; it starts with easy and should become more difficult step by step. There are various features related to the difficulty levels in dance games. As comparing the game logs of player with each other, the game-score for the charts in the same difficulty level greatly differs for each player. If the difficulty level is linear in one dimension, the players should be able to get almost the same game-score for every dance-chart in the same level. That is to say, the difficulty levels of the dance games can be characterized by multiple dimension even though it is labelled as the same difficulty level.

The difficulty levels for rhythm-based video games has not well been studied. The existing mainstream in the research of rhythm-based video games is the thropological study [2] and the Procedural Content Generation (PCG) [3]. *Dance Dance Convolution* [4] proposed by Donahue *et al.* is the typical PCG research for dance games. In their proposed method, the dance-charts are automatically generated from the input music based on an LSTM model with all of the charts in a dataset; though, the dataset includes a mix of dance-charts with varied characteristics. As constructing a model with such diverse data, the characteristics of each data may be averaged. Hence, the dance-chart without any characteristics can be generated for any kinds of input music; this is not good enough as an entertainment application though it is a good study in a field of machine learning. To solve this problem, a model constructed for each characteristics obtained by a dance-charts clustering in advance should show the effectiveness. It is considered that learning charts with specific characteristics may deliver the generation of the charts with the intended characteristics.

This paper designs the track features related to characteristics and conducts a dance-charts clustering. The study on the designed features may lead to the objective evaluation of the dance-charts. The results of clustering should suggest the tendency of charts in the dataset, and it might be applied in the automatic generation of the dance-charts.

II. Related Work

The difficulty level of games has been researched in some existing papers. Wehbe *et al.* studies whether the difficulty level can be changed or not while changing the parameters such as *scroll speed* and *jump task complexity* for simple platformer games [5]. Spiel *et al.* are targeting a puzzle game *TETRIS* and study the effect of the selection algorithm for pieces: they do not focus on the speed of games, which axiomatically affects the difficulty of games [6]. These studies claim that there are multiple parameters related to the difficulty levels of games. Our paper can be regarded as a study to investigate the parameters to be addressed in dance games.

Our previous study was for a PCG method in dance games [7]. The proposed system was based on the LSTM model in which the relationships between easy and difficult charts for the same track were learned. In this paper, the dataset used in the previous study is objectively considered as focusing on not only the difficulty levels but also the characteristics of charts.

978-1-7281-1884-0/19/$31.00 ©2019 IEEE

TABLE I
THE STATISTICS OF THE DATASET

Dataset	ITG
Num authors	8
Num packs	2
Num songs	133
Num charts	652
Publishd year	2004∼2005

III. DATASET

ITG dataset ("In The Groove" and "In The Groove 2"), which is also used in the existing papers [4], [7], is studied in this paper. This includes dance-charts for 133 tracks which are playable on an open-sourced game *Stepmania* [1].

Table I shows statistics of the dataset. The multiple charts for different difficulty levels for a single audio file are included in the dataset. The chart for each difficulty level is named as "Beginner," "Easy," "Medium," "Hard," and "Challenge" in ascending order of difficulty.

IV. FEATURES CHARACTERIZING TRACKS

We heuristically set the following features based on the knowledge of expert players. The features are roughly divided into two categories: **score features** and **song features**. Though the song features are exactly the same for multiple different charts for the same track, the score features differ among charts; the charts differ according to the difficulty level while the song is the same. Some of the features have been mentioned in the existing papers [4], [7]. The analysis target of our study is from the first step to the last step.

A. Score Features

1) Number of Steps Per Second: We divide a chart into the parts for each one second. The following features are obtained by counting the number of steps on each part;

n_l # of steps on the part which has the least steps.
n_m # of steps on the part which has the most steps.
n_μ Average of # of steps through all parts.
n_σ^2 Variance of # of steps through all parts.

2) Jump Steps: We observe steps with two or more arrows at the same timing. Such steps require the player to hit all of the indicated panels at once usually using both feet: those are defined as *jump steps* in this paper.

We obtain the following features by counting the number of jump steps through the chart;

j_r = # of jump steps/# of total steps.
j_d = # of jump steps/Length of the chart [sec].

3) Step Ratio for Each Beat Layer: We address the concept of the "beat layer," which is proposed in our previous paper [7], to express the complexity of rhythm. A set of timing obtained by dividing a bar into q equal parts ($q \geq 4$) is defined as "qth beat layer." Let the lowest layer which the timing where a given step exists belongs to be the qth layer, the step should belong to qth layer and defined as "qth step;" here, "the lowest" means least q. If some steps belong to the higher layer, the sequence of steps should be more difficult and complex. The details of the concept have been described in our previous paper [7].

[1] Stepmania, https://www.stepmania.com, (Retrieved on Jun. 13, 2017)

TABLE II
THE TOP THREE FREQUENT 3-GRAMS OF STEPS

Step 1	Step 2	Step 3	Total Frequency	Chart Count
↑	↓	⟶	4,457	600
↓	↑	↓	4,238	553
⟵	↑	↓	4,216	589

The following features concerning beat layer can be obtained through the calculation of the belongings of each step in the charts;

l_4 = # of steps in 4th layer/# of all steps.
l_8 = # of steps in 8th layer/# of all steps.
l_{12} = # of steps in 12th layer/# of all steps.
l_{16} = # of steps in 16th layer/# of all steps.
l_{24} = # of steps in 24th layer/# of all steps.
l_{32} = # of steps in 32th layer/# of all steps.
$l\_oth = 1 - \sum_{q\in\{4,8,12,16,24,32\}} l_q$.

4) $tf - idf$ of 3-gram Steps: The frequency for the arrows of the continuous 3 steps, i.e. 3-gram, is calculated. The dataset includes 6,910 kinds of 3-gram while 176,279 3-grams are in the dataset. 979 kinds of 3-gram account 90% of all 3-grams and are regarded as the analysis target; the set of those 3-grams is defined as G. Table. II shows the top three frequent 3-grams.

For each $g \in G$, let the frequency in a given chart and the number of the charts in which g is used be tf_g and df_g, respectively. The $tf - idf$ for g can be calculated as s_g according to the following formula;

$$s_g = \frac{tf_g}{\sum_{i\in G} tf_i} \times \log_2 \frac{m}{df_g},$$

where, m denotes the number of charts in the dataset, which is set as 652 in this paper. The s_g shows the identity of the 3-gram for the chart.

B. Song Features

1) Tempo: The data in the dataset has the tempo of the song, which is shown as beat per minute (BPM). When the tempo changes in a song, the timing of the changing and the changed tempo are shown in the data. For *Stepmania*, the faster the tempo is the faster the moving speed of steps is. Players have to have quick decisions and actions for the faster song, it is thus considered that the faster song is more difficult. The changing of tempo in a song may change the moving speed of steps which is usually uniform motion. It can be assumed as a "gimmick" that is hard to expect for the players.

The following features concern the tempo of the song. The value for the features is the rounded integral BPM excepting t_μ;

t_l The tempo which covers the longest time in a chart.

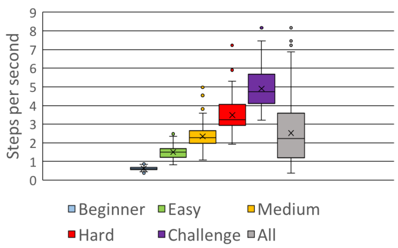

Fig. 1. A box plot concerning the distribution of n_μ for each difficulty level.

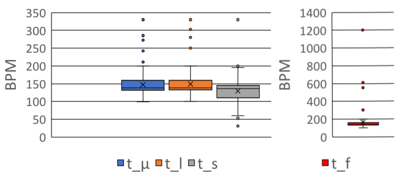

Fig. 2. A box plot concerning the distribution of t_μ, t_l, t_s and t_f. Note that the plot of t_f has different scale from the others.

- t_s The slowest tempo in a chart.
- t_f The fastest tempo in a chart.
- t_μ = # of all beat/the length of a song [sec] $\times$ 60.

The features concerning the changing of the tempo are as follows;

- t_r $= t\_f / t\_s$.
- t_n # of the changing tempos
- t_t # of the changing tempos where the changing rate is 2^m ($m \in \mathbb{Z}$ and $m \neq 0$): this change can be assumed as the tempo change intending only moving speed of steps.

2) Pause Gimmicks: Pause gimmick is set in some charts, which pause the movement of the steps during the intended time period; this works as same as the changing of tempo. The following feature concerns the pause gimmick;

- p_n # of the pause gimmicks in a chart

V. Statistical Analysis for Each Feature

The features described in section IV for all of the charts in ITG dataset are statistically analyzed. For lack of space, the remarkable discussions are detailed in this paper: n_μ and the features related to tempos, i.e., t_μ, t_l, t_s and t_f.

Fig. 1 shows the box plot concerning the distribution of n_μ for each difficulty level and all of the charts. And, Fig. 2 shows the box plot concerning the distribution of t_μ, t_l, t_s and t_f. For these analyses, we treat the values which are higher than $Q_3 + 1.5(Q_3 - Q_1)$ or lower than $Q_1 - 1.5(Q_3 - Q_1)$ as outliers, where Q_3 is third quartile and Q_1 is the first quartile. The discussions for these results will be shown in the following sections.

A. Average of Step Frequency Per One Second

From Fig. 1, it was confirmed that the more the difficulty level increased the higher the average of step frequency was. Also, the interquartile range became wider according to the increment of the difficulty level. These results suggested that the frequency of the steps differed for each chart in the difficult levels though the one would resemble for each other in the easy levels.

As an interesting point, we confirmed that there were outliers in the Medium and Hard levels which values were higher than the third quartiles of each corresponding one level higher. It is not too much say that those charts could be, leastwise from the aspect of n_μ, assumed as the improperly difficult charts for the intended levels.

B. Tempo

With the t_μ and t_l in Fig. 2, it was confirmed that the tempos for half of the songs in the dataset were in the range between 130 and 160 BPM. However, there were some tracks which exceptionally had a higher tempo. The tempo of a song "*Pandemonium*" is not changed through the song and is 330 BPM, i.e., $t\_s = t\_f = 330$. Especially for t_s, the value is extremely outlier. Though the t_l of a song "*Robotix*" is just 150, the tempo gradually increases from the middle of the song until the tempo becomes 1,200 and then decreases. Its t_f is extraordinarily out of the range for other songs.

VI. Dance-Charts Clustering

In order to conduct a dance-charts clustering, the following four types of feature vectors, which were composed of the features described in section IV, were generated for each chart;

$$\boldsymbol{n} = (n\_l, n\_m, n\_\mu, n\_\sigma^2, j\_r, j\_d).$$
$$\boldsymbol{l} = (l_4, l_8, l_{12}, l_{16}, l_{24}, l_{32}, l\_oth).$$
$$\boldsymbol{s} = (s_g | g \in G).$$
$$\boldsymbol{t} = (t\_\mu, t\_l, t\_s, t\_f, t\_r, t\_n, t\_t, p\_n).$$

Principal Component Analysis (PCA) was applied for each feature vector. All of the PC for $\boldsymbol{n}, \boldsymbol{l}$ and $\boldsymbol{t}$ were accepted to the PC vectors $\boldsymbol{pc\_n}, \boldsymbol{pc\_l}$ and $\boldsymbol{pc\_t}$ which had the same dimension with the corresponding vector. The dimensional number of $\boldsymbol{s}$ was too big: 952. Thus, the top PCs were accepted in reference to the contribution ratio until the cumulative contribution ratio covered 90%, and the 208-dimensional PC vector $\boldsymbol{pc\_s}$ was obtained. As the $\boldsymbol{pc\_n}, \boldsymbol{pc\_l}, \boldsymbol{pc\_s}$, and $\boldsymbol{pc\_t}$ were conjoined, the 229-dimensional feature vector for the chart was obtained and used in the clustering. We used the k-means method as the clustering method. While the number of clusters k was changed in the range between 3 and 12, the clustering was conducted with the feature vectors above. This paper detailed the study of the clustering with $k = 4$ and 6 for lack of space.

Table III and IV each shows the result of the dance-charts clustering with $k = 4$ and $k = 6$, respectively; we heuristically set the cluster ID as the similar clusters had the same ID beyond the tables. From both of the results, it was confirmed that there were the majority clusters with more than 100 charts and the minority clusters with less than 25 charts. Without difference of the k, the clusters in which the tendency of the features was similar were obtained beyond those results, e.g., $n\_\mu \approx 1.1$ and $l_4 \approx 100\%$ for cluster 0 in both of the

TABLE III
RESULT OF THE DANCE-CHARTS CLUSTERING ($k = 4$)

Cluster ID	# of Charts	Average of Each Metrics n_μ	l_4	l_8	l_{16}	t_μ	Cluster Summery
0	278	1.142	97.8%	2.1%	0.0%	142.249	Less steps. Mostly the 4th-layer steps.
1	223	2.849	65.5%	29.1%	4.7%	143.274	Moderate number of steps. Mostly 4th and 8th layer steps.
2	126	4.786	40.7%	33.4%	23.8%	144.595	Much steps. 16th layer steps are frequent.
3	25	3.675	78.2%	17.2%	2.6%	268.202	The high tempo.

TABLE IV
RESULT OF THE DANCE-CHARTS CLUSTERING ($k = 6$)

Cluster ID	# of Charts	Average of Each Metrics n_μ	l_4	l_8	l_{16}	t_μ	Cluster Summery / Other Notable Metrics
0	227	1.069	98.4%	1.6%	0.0%	142.843	Less steps. Mostly the 4th-layer steps.
1	199	2.221	77.4%	20.3%	2.1%	140.777	Moderate number of steps. Mostly 4th and 8th layer steps.
2	200	4.387	45.7%	34.7%	18.2%	147.571	Much steps. 16th layer steps are frequent.
3	23	3.325	79.4%	15.5%	2.8%	262.826	The high tempo.
4	2	4.064	45.5%	0.0%	0.0%	139.992	$l_{12} = 54.6\%$ (in average).
5	1	1.009	94.6%	5.4%	0.0%	139.993	"*Bend Your Mind*" (Easy) including 12 triple steps.

clustering results. Note, we will describe the discussions for both of the results if a specific k is not mentioned below.

A. Discussions for Majority Clusters

Cluster 0, 1 and 2 included more than 100 charts. The n_μ of cluster 2 is the highest and followed by cluster 1 and 0. For cluster 0, it was confirmed that $l_4 \approx 100\%$, and there was almost no step in the 8th and 16th layers. Though the l_8 for cluster 1 was higher than the one for cluster 0, its l_{16} remained low in value. The l_{16} for cluster 2 was higher than both cluster 0 and 1. Accordingly, these three clusters differed in the number of steps and the active beat layer. Although we conducted the clustering with $k > 6$, we did not find the difference of tendency for these three majority clusters for each k.

It was confirmed that some of the charts in different difficulty levels were clustered to the same cluster: e.g., cluster 1 with $k = 4$ included 12 Easy, 94 Medium, 97 Hard and 20 Challenge charts. That is to say, the clustering results showed that the charts that have similar features existed beyond the difficulty levels.

B. Discussions for Minority Clusters

Cluster 3 included only five tracks with specific tempo features, which were the outlier with t_μ in Fig. 2. It was thus suggested that the cluster 3 consisted of the charts with the exceptionally high tempo were gathered without difference of the difficulty levels.

For the result with $k = 6$, few charts constructed a cluster. Cluster 4 consisted of only Hard and Challenge charts of "*We Know What To Do*." Only these two charts showed $l_{12} > 50\%$, and the follow-up chart showed $l_{12} = 12\%$. Cluster 5 consisted of Easy chart of "*Bend Your Mind*" by itself. This chart included so many steps that required more than three panels were stepped at one time. Therefore, this chart included many 3-gram that did not appear in other charts; the $\boldsymbol{pc\_s}$ might characterize this chart. As in a case with $k > 6$, it was confirmed that some of the charts in the majority cluster constructed new minority clusters.

VII. CONCLUSION

This paper designed chart features related to the characteristics of the charts and conducted a dance-charts clustering. It was confirmed that the designed features differed among the difficulty levels. Also, we objectively found that some tracks had exceptionally extreme characteristics. Based on the designed features, the tracks were clustered depending on the step frequency and complexity of rhythm, and the outliers composed a cluster themselves.

Minority clusters will be addressed in the future. The minority cluster consisted of few tracks, and those should be assumed as not clusters but just outliers. Although the k increases, it just brings much more minority clusters. Those tracks or charts should be removed from the clustering beforehand; that is to say, data cleansing for the charts should be conducted in advance. Then, the clustered charts will be able to be effectively used as learning data for automatic generation of dance-charts.

REFERENCES

[1] K. Salen and E. Zimmerman, *Rules of Play: Game Design Fundamentals*. The MIT Press, 2004.

[2] B. G. Behrenshausen, "Toward a (kin)aesthetic of video gaming: The case of Dance Dance Revolution," *Games and Culture*, vol. 2, no. 4, pp. 335–354, 2007.

[3] N. Shaker, J. Togelius, and M. J. Nelson, *Procedural Content Generation in Games: A Textbook and an Overview of Current Research*. Springer, 2016.

[4] C. Donahue, Z. C. Lipton, and J. McAuley, "Dance Dance Convolution," in *Proc. of ICML 2017*, 2017, pp. 1039–1048.

[5] R. R. Wehbe, E. D. Mekler, M. Schaekermann, E. Lank, and L. E. Nacke, "Testing incremental difficulty design in platformer games," in *Proc. of the 2017 CHI*, 2017, pp. 5109–5113.

[6] K. Spiel, S. Bertel, and F. Kayali, ""Not another Z piece!" adaptive difficulty in TETRIS," in *Proc. of the 2017 CHI*, 2017, pp. 5126–5131.

[7] Y. Tsujino and R. Yamanishi, "Dance Dance Gradation: A generation of fine-tuned dance charts," in *Entertainment Computing – ICEC 2018*, 2018, pp. 175–187.