Kinematic analysis of movement by using deep learning

Zijie Song

RCF experimental school, Beijing, 100028, China

13021100015@163.com

Abstract. The aesthetic standard for unconventional dances such as K-pop and ACGN dance does not follow the qualitative standard for traditional dances such as Ballet and modern dance. However, differential equations, motion capture, and computer vision can be used to quantitatively analyze these newly formed dances. Therefore, in the research, we use the AI method to extract and construct dance 3D poses and analyze the key points in dance by using PCA. The results indicate that PCA can identify the quality of dance. Moreover, the use of kinematics in dance aesthetics is considered to be effective.

Keywords: Kinematics, Dance, K-pop, ACGN, Deep Learning, and PCA.

1 Introduction

In recent years, Korean pop (K-pop) and Anime, comics, games, and novels (ACGN) dance gained popularity among the public. K-pop and ACGN dance are two nontraditional dance types. K-pop dance originated in South Korea [1-3], and ACGN dance originated in Japan [4]. K-pop dance is based on Korean music and is largely spread on digital platforms, such as YouTube and BiliBili [5]. ACGN dance is also largely spread on digital platforms due to its anime-based nature. However, compared to K-pop and ACGN dance, traditional dances such as ballet and modern dance are largely based on theater instead of digital media. Ballet originated in modern-day northern Italy [6], and modern dance originated in 20th-century America [7]. Ballet movement has various styles such as classical ballet, romantic ballet, neoclassical ballet, and so on, and modern dance movement has a feature of contraction and release [8]. Due to their standardized movement features, ballet and modern dance can be analyzed using kinematics. One analysis includes the kinematics of passive hip external rotation in five classical ballet positions [9]. Other analyses contain the flexion in lower-limb structure of plié and the intensity differences in legs of Fouetté Turn [10-11]. The kinematic analysis of modern or contemporary dance contains the landing technique, the effect on postural stability, and the effect on aesthetic evaluation [12-14]. Compared to traditional dances, unconventional dances such as K-pop and ACGN dance have less standardized movement features. The lack of a standardized dance pattern in K-pop and ACGN dance causes less analysis of kinematics in K-pop and ACGN dance.

The impression of K-pop dance is related to body movement, body gesture, and appearance [15]. On the one hand, body performance, which includes body movement

Y. Li et al. (eds.), *Proceedings of the 2024 3rd International Conference on Science Education and Art Appreciation (SEAA 2024)*, Advances in Social Science, Education and Humanities Research 866,
https://doi.org/10.2991/978-2-38476-291-0_23

and gesture, can influence audiences' impressions. For example, synchronized and fast paced movements among a K-pop dance group are considered to have a positive impression [16]. On the other hand, K-pop dancers' appearance can affect the impression. Different members in a K-pop group have distinct customs, but all members can reach a harmony in their customs for the audience to have a positive impression [17]. Although the relationship between the impression of ACGN dance and dancers' movements is rarely investigated, the impression of ACGN dance can be affected by subjective factors. ACGN dance is a dance based on ACGN culture, so the impression of ACGN dance could possibly be affected by ACGN culture. These factors of impression of dance are based on sensible experience. The impression of K-pop and ACGN dance is mostly affected by subjective factors, including body performance, appearance, and culture. However, very few quantitative methods are used to analyze K-pop and ACGN dance. In this work, we focus on quantitative tools to analyze kinematic parameters and try to give K-pop and ACGN dance a new perspective to understand the impression of dance.

Evaluation and analysis of dance movement quality are crucial for dance teaching and choreography. Former researchers constructed dance performance systems based on qualitative methods. For example, the World Dance Sport Federation provided qualitative criteria for dancers. These standards include posture, timing, basic rhythm, body line, and so on. All of these are based on qualitative observations, which are difficult for a nonexpert, such as a normal audience, to understand and judge. Moreover, researchers in dance already felt that the qualitative evaluation method is not enough [18]. Therefore, using quantitative tools to analyze dance, especially newly fashioned K-pop and ACGN dance, is an inevitable method for the dance industry.

Benefiting from the rapid development of motion capture systems and computer vision, dance performances gain effective tools in movement analysis. Motion capture is used in fields such as healthcare, video games, robotics, sports, and even the art industry [19]. Dance, which is part of the art industry, is also widely investigated by motion capture. Motion capture, a method that can track object movement, can store the movement in digital form [20]. Usually, motion capture techniques fall into two types: active and passive. The active method means the sensors or markers on moving objects can emit signals to establish movement, and the passive method means the movements are captured using only images. For example, a motion capture system can be used to detect the movements of students in class [21], to identify different dance poses [22], and to understand the underlying choreography pattern in dance [23]. However, the problem behind motion capture is the high cost of setting up the capture environment and capturing sensors.

Instead of motion capture systems, computer vision, such as the deep learning method, has gained attention in dance analysis in recent years. Deep learning can be considered a neural network with multiple layers, and it can be used to handle large datasets [24]. Deep learning is useful in lots of industries, including dance. Dance movement patterns vary based on cultural and ethnic differences [25]. In dance classification, the differences in dance types need to be detected precisely. The subtle distinctions in dance styles can only be seen when dancers undergo an in-depth study. Consequently, it is not possible for one expert to learn all the dance styles and classify them. However, deep learning is able to classify the various dance types [26]. Deep learning has the great advantage of extracting complicated characteristics from original data and can study different dance styles efficiently [25]. In addition, deep learning can also be used to generate dance movements, which is choreography [27]. Due to the large datasets that deep learning can handle, it can generate a single dance pattern with diverse styles [27]. All in all, the application of computer vision, specifically deep learning, in the dance industry is highly effective.

In this work, we analyze the kinematic parameters of nontraditional dance types and try to find the correlation between dance impression and kinematic data. First, we take videos of K-pop and ACGN dances from video streaming. Then, by applying the deep learning method to dance videos, we extract human 3D pose variations throughout the video [28]. Finally, the 3D poses are analyzed by using principal component analysis (PCA). PCA is a method that deals with a dataset by describing the relationship between multiple variables [29]. PCA can amplify the differences between sets of data. In the case of dance, the difference in the movement of key points can be enlarged.

2 Method

First, we have to establish a 2D pose model. Without the use of any key point detector, Mask R-CNN and the Mask' s reference implementation among Detectron is used to extract the 2D key points from video streams [28]. Second, the 3D pose model is extracted from the 2D pose model. VideoPose3D works by inputting 2D poses dataset and making poses go through the process of temporal convolutions. The convolutional model makes a synchronization for the batch and the time. Also, a convolutional model can control the temporal receptive field accurately, and the accuracy can then be used for the extraction of 3D poses [28]. The transformation model used in the research is based on training 3D poses in camera space and modifying poses in terms of camera transformation [28].

Coordinate variability in 3D poses can be assessed by PCA. Movement patterns in dance are limited by various external factors, including motile ability, task difficulty, music style, physical constraints, and so on. For example, movements like walking, jumping, rotating, and rolling all have their own typical movement patterns in time and space. These typical movement patterns imply that the DOF in human movements is reduced and integrated into a specific pattern, allowing humans to carry out movement tasks. The initial DOF has a significantly higher number than the limited version. To be more specific, the DOF is formed from the connected movements of joints. In addition, when the same dance combo is danced by different dancers, who can have distinct flexibility, explosive power, or movement styles, the movement pattern may be hard to identify. An effective method for identifying the characteristic is to use quantifiable key points to build up and visualize a complex dance movement pattern. Therefore, we suggest that principal component analysis can be used to deconstruct the complex dance movement pattern and analyze the characteristic differences among the set of dance videos by reducing the DOF. PCA is a method that deals with a dataset by describing the relationship between multiple variables [29-32]. Several steps are involved in the application of PCA. First, the data is standardized. Data are transformed into similar scales to reduce the possibility of biased results. Second, the covariance matrix is calculated. The covariance matrix can help identify the correlation between variables in input data. Then, the eigenvector and eigenvalue of the covariance matrix are calculated. The eigenvector and eigenvalue are able to distinguish the principal component from all the data by compressing most of the data of the considered variable into the first principal component. Finally, the data for the selected principal components is displayed on the graph and used for the analysis.

3 Experiment and Result

To begin with, data is collected from the online platform "BiliBili". The Windows Screen Recording function is used to record videos from the internet. The chosen videos include three K-pop and three ACGN dances. For each dance combo, 10 videos are recorded. Accordingly, the experiment involves a total of 60 videos. Secondly, the recorded videos are edited by the software "Filmora" by Wondershare. For all the videos, only theme dance sections are recorded, so the time length of the data used varies from 13 to 23 seconds, and the frame number of the data used ranges from 295 to 565. Throughout the subjective evaluation of the dances, the negative and positive samples are identified. The percentages of sample quality are illustrated in the following: K-pop dance 1: 40% negative and 60% positive; K-pop dance 2: 40% negative and 60% positive; K-pop dance 3: 40% negative and 60% positive; ACGN dance 1: 40% negative and 60% positive; ACGN dance 2: 20% negative and 80% positive; ACGN dance 3: 30% negative and 70% positive. NumPy is used to analyze the data and construct the PCA. First, the 17 skeleton key points are connected in pairs to form vectors. Then, throughout the pairing of vectors, the angles between vectors are established and analyzed. The following equation is used to calculate the angle between two vectors, for which v1 is one vector and v2 is another vector.

$$\theta = \cos^{-1} \frac{\overrightarrow{v1} \cdot \overrightarrow{v2}}{|\overrightarrow{v1}| \cdot |\overrightarrow{v2}|} \tag{1}$$

Moreover, the first derivative of angle variation is calculated and analyzed.

Figure 1 illustrates the skeleton construction from video to 3D pose and the K-pop dance "Pink Venom" by BLACKPINK. On the left, Detectron precisely extracted the dancer' s 2D poses. On the right, a 3D pose is constructed by VideoPose3D. Considering only the key points, we can only see the distribution of key points in space and time, not the clear dance pose. With the 3D pose and the lines that connected the key points, the dance pose is seen. Moreover, when viewing in 3D, we can also observe the angles constructed by lines. Although the inaccuracy in constructing a 3D model due to the low quality and moving camera of the videosConsequently, it can be suggested that geometrically continuous shapes like angles and lines account for the subjective perception of dance poses.

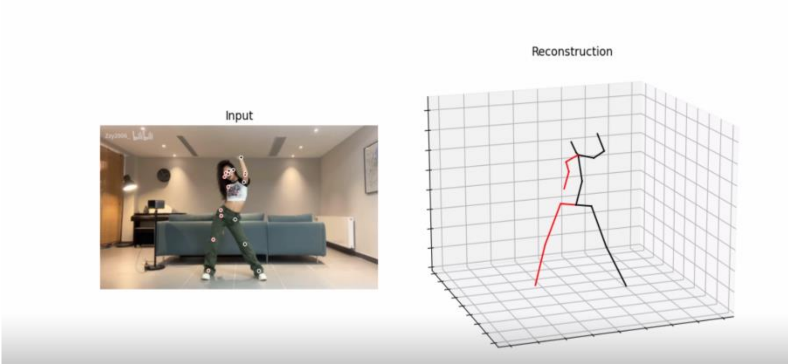

Fig. 1. left: dance video and 2D pose; right: constructed 3D pose

In addition, for all the dance videos, the angles formed by connected lines do not vary as the scale of the video changes. Therefore, choosing angles as the considered variable in dance impression can eliminate confounding factors such as individual displacement and dancer scale in video.

For all the dance videos, blue represents the bad impression video, whereas red represents the good one. ACGN dance 1 is the most typical of all. Two graphs with PCA 0 and 1 dimensions are illustrated. Fig. 2 is the characteristic of a bad-quality dance video, whereas Fig. 3 is that of a good-quality dance video. The distribution of absolute angle data is different based on quality. The blue dots scattered in a spindle shape, but the red dots scattered in a sector shape.

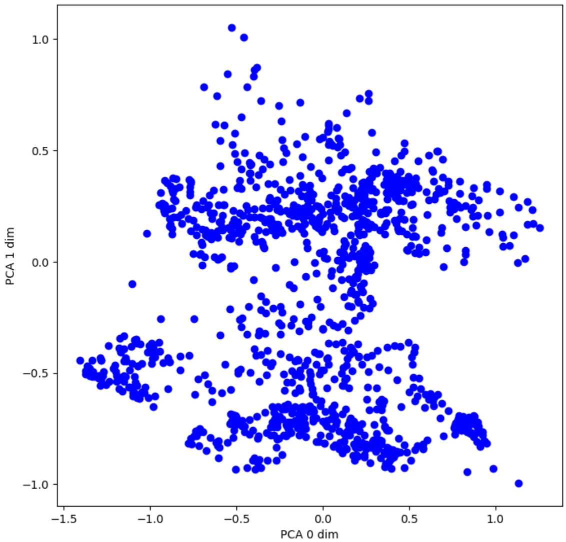

Fig. 2. Bad quality ACGN dance 1

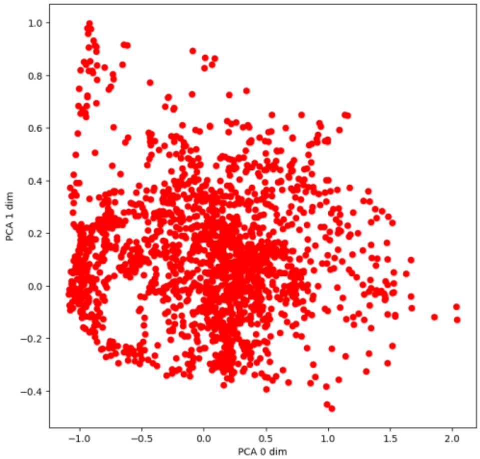

Fig. 3. Good quality ACGN dance 1

In addition, the first derivative of angle variation also shows a difference. Fig. 4 and Fig. 5 are graphs for the first derivative of angle variation. First, the distribution of blue dots has a negative gradient when considered as the line of best fit, whereas that of red dots has a positive gradient. Second, the blue dots have bigger variations in the distribution on the PCA dim 0 than that of the red dots. This comparison may imply that good-quality dances tend to a same type of movement pattern, whereas bad-quality dances are the opposite. In all, both analyses indicate that PCA has the ability to quantitatively distinguish good-quality dances from bad-quality dances in the realm of nontraditional dances. Also, the kinematic parameter, which is the angle, is considered to be an effective standard in dance aesthetics.

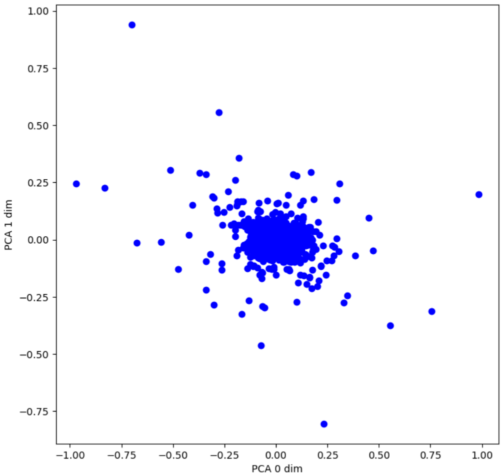

Fig. 4. Bad quality dance for first derivative

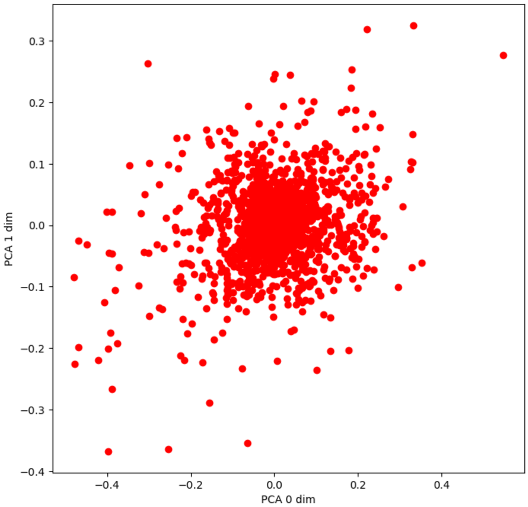

Fig. 5. Good quality dance for first derivative

4 Conclusion

In the research, we use the AI method to extract and construct dance 3D poses and analyze the key points in dance by using PCA. The results indicate that for both K-pop and ACGN dances, PCA has the ability to identify bad quality dances from good ones, and the use of kinematics in dance aesthetics is considered to be effective. Moreover, by comparing the PCA graphs for angle variation and first derivative, we find a consistent difference between the bad and good quality dances. However, the underlying mechanism that affects the movement characteristic variation needs further research. Overall, PCA is able to identify dance aesthetics and even distinguish between two nontraditional dance types, which are K-pop and ACGN dances.

References

1. D. Kim, D. H. Kim, and K. C. Kwak, “Classification of K-pop dance movements based on skeleton information obtained by a kinect sensor,” Sensors (Switzerland), vol. 17, no. 6, 2017, doi: 10.3390/s17061261.
2. Xie Jingwen, Wang Weixing, Ma Liandan, et al. Research on digital protection of primitive dance based on bone information [J]. Computer Age, 2023(9):136-141.
3. Huang Pan, Zhang Yu. Automatic recognition System of Folk dance movement based on Motion Capture Sensor [J]. Automation & Instrumentation, 2022(008):000.
4. Z. T. Chen, “Poetic prosumption of animation, comic, game and novel in a post-socialist China: A case of a popular video-sharing social media Bilibili as heterotopia,” J. Consum. Cult., vol. 21, no. 2, pp. 257–277, 2021, doi: 10.1177/1469540518787574.

5. I. Oh and H.-J. Lee, “K-pop in Korea: How the Pop Music Industry Is Changing a Post-Developmental Society,” Cross-Currents East Asian Hist. Cult. Rev., vol. 3, no. 3, pp. 72–93, 2014, doi: 10.1353/ach.2014.0007.
6. H. Wulff, “Ethereal expression: Paradoxes of ballet as a global physical culture,” Ethnography, vol. 9, no. 4, pp. 518–535, 2008, doi: 10.1177/1466138108096990.
7. M. Thompson and F. Shott, “The History of Modern Dance,” Ballet Austin, pp. 1–10, 1998, [Online]. http://www.presentfocus.com/Articles/Mind-Body/Movement/Movement.pdf
8. I. Matte Blanco, “Formulation of the Problem,” Unconscious as Infin. Sets, vol. 3, no. 23, pp. 399–408, 2018, doi: 10.4324/9780429483592-35.
9. J. Gorwa, J. Kabaciński, M. Murawa, and A. Fryzowicz, “On the track of the ideal turnout: Electromyographic and kinematic analysis of the five classical ballet positions,” PLoS One, vol. 15, no. 3, pp. 1–16, 2020, doi: 10.1371/journal.pone.0230654.
10. K. N. abill. S. Gontijo, C. T. Candotti, G. D. o. S. Feijó, L. P. aixã. Ribeiro, and J. F. agunde. Loss, “Kinematic evaluation of the classical ballet step ‘plié,’” J. Dance Med. Sci., vol. 19, no. 2, pp. 70–76, 2015, doi: 10.12678/1089-313X.19.2.70.
11. A. Imura, Y. Iino, and T. Kojima, “Kinematic and kinetic analysis of the fouetté turn in classical ballet,” J. Appl. Biomech., vol. 26, no. 4, pp. 484–492, 2010, doi: 10. 1123/ jab. 26.4.484.
12. Y. Jones, “Comparison of Ballet and Modern Dance in terms of Kinetics , Kinematics and Muscle Activation during Landing for College Dancers,” pp. 1–77, 2015.
13. D. Marinkovic, A. Belic, A. Marijanac, E. Martin-Wylie, D. Madic, and B. Obradovic, “Static and dynamic postural stability of children girls engaged in modern dance,” Eur. J. Sport Sci., vol. 22, no. 3, pp. 354–359, 2022, doi: 10.1080/17461391.2021.1922503.
14. C. Torrents, M. Castañer, T. Jofre, G. Morey, and F. Reverter, “Kinematic parameters that influence the aesthetic perception of beauty in contemporary dance,” Perception, vol. 42, no. 4, pp. 447–458, 2013, doi: 10.1068/p7117.
15. T. A. Perdini, T. Supriyadi, E. S. H. Hutahaean, and Y. W. Pertiwi, “International Journal of Multicultural and Multireligious Understanding Self-Presentation Analysis of the K-POP Dance Cover Community Member,” pp. 139–149, 2022.
16. Y. S. B, Proceedings of the 2022 International Conference on Science Education and Art Appreciation (SEAA 2022). Atlantis Press SARL, 2023. doi: 10.2991/978-2-494069-05-3.
17. A. E. Necula, “Restored behavior in K-pop performances . Liminal experience , fantasy , the American influence , and how to overcom ...,” no. January, 2022.
18. D. Krasnow and S. J. Chatfield, “Development of the ‘performance competence evaluation measure’: assessing qualitative aspects of dance performance.,” J. Dance Med. Sci., vol. 13, no. 4, pp. 101–107, 2009.
19. M. Menolotto, D. S. Komaris, S. Tedesco, B. O’flynn, and M. Walsh, “Motion capture technology in industrial applications: A systematic review,” Sensors (Switzerland), vol. 20, no. 19, pp. 1–25, 2020, doi: 10.3390/s20195687.
20. G. David and A. Sousa, Doctoral Symposium in, no. January. 2012.
21. J. C. P. Chan, H. Leung, J. K. T. Tang, and T. Komura, “A virtual reality dance training system using motion capture technology,” IEEE Trans. Learn. Technol., vol. 4, no. 2, pp. 187–195, 2011, doi: 10.1109/TLT.2010.27.
22. E. Protopapadakis, A. Voulodimos, A. Doulamis, S. Camarinopoulos, N. Doulamis, and G. Miaoulis, “Dance Pose Identification from Motion Capture Data: A Comparison of Classifiers,” Technologies, vol. 6, no. 1, p. 31, 2018, doi: 10.3390/technologies6010031.
23. K. Vincs and K. Barbour, “Snapshots of complexity: using motion capture and principal component analysis to reconceptualise dance,” Digit. Creat., vol. 25, no. 1, pp. 62–78, 2014, doi: 10.1080/14626268.2013.786732.

24. S. A. Bini, “Artificial Intelligence, Machine Learning, Deep Learning, and Cognitive Computing: What Do These Terms Mean and How Will They Impact Health Care?,” J. Arthroplasty, vol. 33, no. 8, pp. 2358–2361, 2018, doi: 10.1016/j.arth.2018.02.067.
25. X. Liu and Y. C. Ko, “The use of deep learning technology in dance movement generation,” Front. Neurorobot., vol. 16, no. Dl, 2022, doi: 10.3389/fnbot.2022.911469.
26. S. Biswas, A. Ghildiyal, and S. Sharma, “Classification of Indian Dance Forms using Pre-Trained Model-VGG,” 2021 Int. Conf. Wirel. Commun. Signal Process. Networking, WiSPNET 2021, pp. 278–282, 2021, doi: 10.1109/WiSPNET51692.2021.9419426.
27. J. Li et al., “Learning to Generate Diverse Dance Motions with Transformer,” pp. 1–9, 2020, [Online]. Available: http://arxiv.org/abs/2008.08171
28. D. Pavllo, C. Feichtenhofer, D. Grangier, and M. Auli, “3D human pose estimation in video with temporal convolutions and semi-supervised training,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2019-June, pp. 7745–7754, 2019, doi: 10. 1109/ CVPR.2019.00794.
29. H. Abdi and L. J. Williams, “Principal component analysis,” Wiley Interdiscip. Rev. Comput. Stat., vol. 2, no. 4, pp. 433–459, 2010, doi: 10.1002/wics.101.
30. Greenacre, Michael, et al. "Principal component analysis." Nature Reviews Methods Primers 2.1 (2022): 100.
31. Kherif, Ferath, and Adeliya Latypova. "Principal component analysis." Machine learning. Academic Press, 2020. 209-225.
32. Gewers, Felipe L., et al. "Principal component analysis: A natural approach to data exploration." ACM Computing Surveys (CSUR) 54.4 (2021): 1-34.