KINEMATIC ANALYSIS OF POP DANCE CHOREOGRAPHIES THROUGH MODULAR MOTOR SYNERGY

Keli Shen[1] and Jun-ichiro Hirayama[1]

AIST, Tsukuba, Japan [1]

Pop dance, or popping, is a subgenre of hip hop dance popularized during the last decades, while its biomechanics is not well understood yet. This study aimed to understand pop dance motions through modular motor synergy analysis. Pop dance performance by three experienced dancers, measured with a markerless human pose estimation method, was analyzed with principal component analysis (PCA) to extract motor synergies. The synergies obtained indicated the movement complexity and specific motor coordination patterns of ten typical pop dance choreographies, with emphasis on elbow, shoulder, hip and knee contributions. The results will enhance our understanding of complex dance movements, making a step toward future applications to medicine or art.
KEYWORDS: motor synergy, joint contributions, motion complexity, coordination, dance.

INTRODUCTION: Pop dance or popping is a subgenre of hip hop dance, characterized by quick contraction and relaxation of muscles to produce jerking of various joints (Ojofeitimi et al., 2012). As a specific instance of complex music-induced movements, analyzing its biomechanics will enhance our understanding of complex human motor behaviors affected by external environments. It has conventionally been challenging to analyze dance movements including pop dance due to the movement complexity as well as the lack of suitable motion datasets. Recently, markerless human pose estimation methods like OpenPose were increasingly used as a practical option for acquiring large amounts of 3D motion data from complex dance movements (Labuguen et al., 2020). Motor synergy has been seen as an efficient hypothesis for understanding simple human motion behavior such as standing balance, walking, and sit-to-stand. Few previous works focused on dance movement synergy analysis with maker-based motion datasets. Bronner et al. (2015) compared the dance performance between expert and intermediate ballet dancers through synergy reconstruction variability. Toivianen et al. (2010, 2022) analyzed spontaneous dance movements through spatial motor synergy calculated by PCA and found that dance moves can be associated with music fluctuation and metrical levels. However, there is still no research on the synergy analysis of pop dance. Here, we aim to understand the motion complexity and motor coordination of pop dance choreographies through modular motor synergies, computed from high-dimensional joint space dance motions induced by music beats. Our study on pop dance synergy analysis contributes to the literature on dance biomechanics.

METHODS: Multi-view video data of pop dance by three dancers were available from the AIST Dance Video Database (Tsuchida et al., 2019). The three dancers (two males and one female, age: 20−25) had 6, 7, and 14 years of dance experience. Each dancer performed ten typical pop dance choreographies, namely fresno, walk out, loft, hand wave, body wave, neck-o-flex, flex, walk, old man, and roll, at four different music tempos per choreography. The beat per minute (BPM) was one of 80, 90, 100, 110, 120, and 130. Kinematic parameters in this database were previously estimated by a markerless method and made available in the AIST++ dance dataset (Li et al., 2021). In our analysis, the 3D joint angles obtained in the axis-angle format were first translated into the Euler-angle format. Then, we segmented the joint angle data into trials based on the timing of the music beats identified through librosa (McFee et al., 2015). A root joint was excluded in our analysis and the remaining 23 joints (69 degrees of freedom) were used in the synergy extraction of dance movements. Motor synergy was computed by PCA based on the hundreds of motion segments from the twelve motion sequences per choreography. The following reconstruction error w.r.t W and C, is minimized by PCA:

$$E^2 = ||M - W \cdot C||_F^2, \quad (1)$$

where $|| \cdot ||_F$ denotes the Frobenius norm; the matrices of joint angles, motor synergies, and activation weights are denoted by M , W, and C, respectively. Given an optimal W with orthonormal columns, simplified synergy representations were obtained by taking square roots of the sum of squares of either the three or six entries in each column of W if symmetric joints do not exist or exist in the right and left sides, respectively, to simplify the interpretation of dance motion parameters related to joint angles.

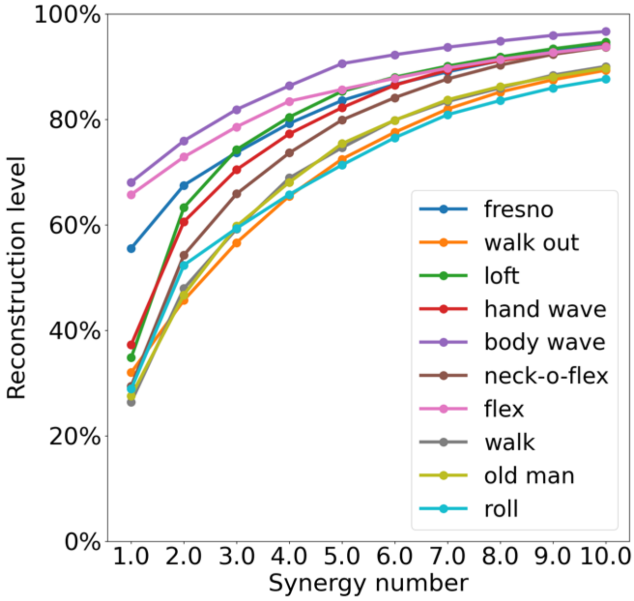

Figure 1: Reconstruction levels of the ten pop dance choreographies at given numbers of synergies. The curves are used for comparing and understanding the complexity of choreographies.

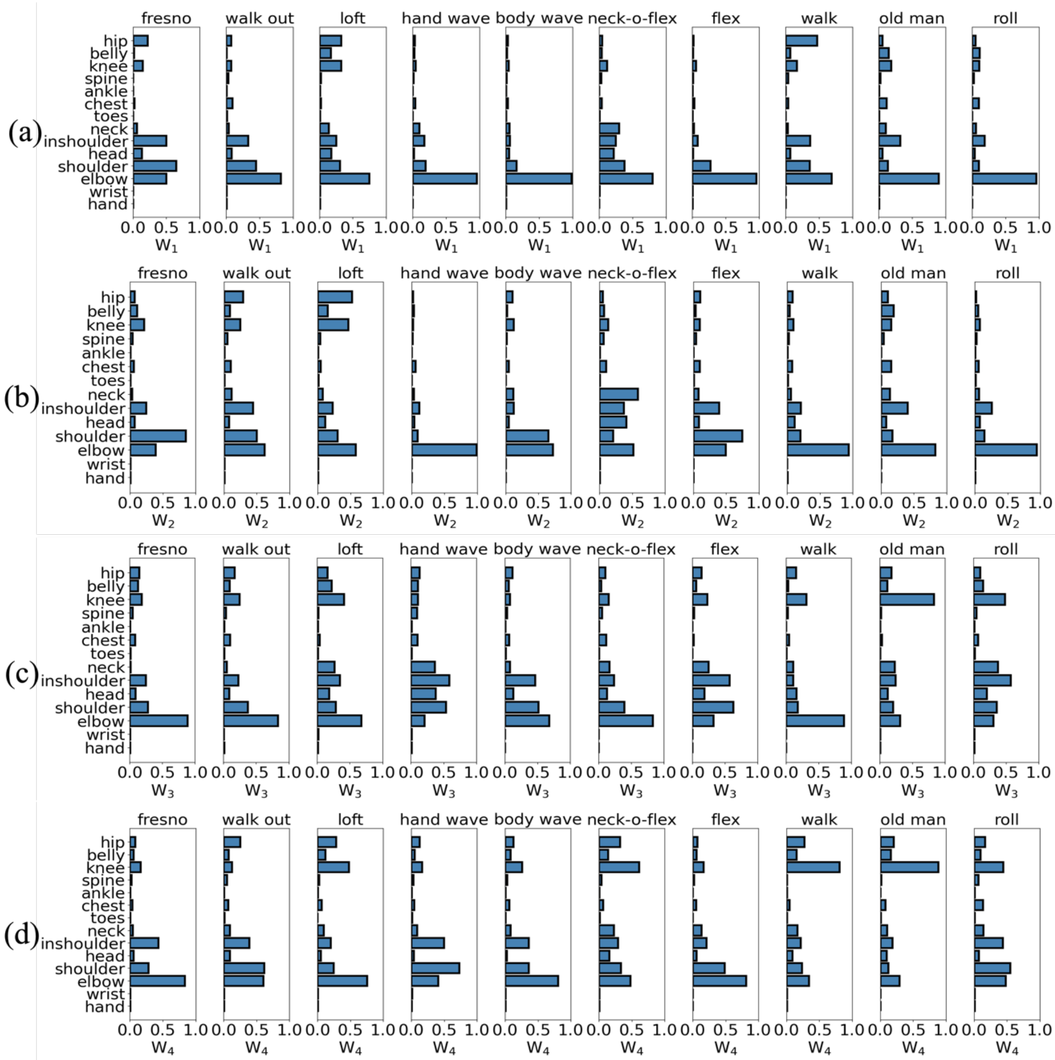

Figure 2: Motor synergies W_1, W_2, W_3 and W_4 of the ten pop dance choreographies computed by PCA. The summarized synergy weights for 1st, 2nd, 3rd and 4th PCs are given in (a), (b), (c), and (d), respectively.

Figure 3: Key frames of the ten pop dance choreographies extracted by DeepLabCut with the K-means algorithm.

This also avoids the arbitrariness in the sign of each column of W. These summarized synergy scores can be used to analyze the modular coordination of dance movements. Given the solution by PCA, the reconstruction level R^2 is given by

$$R^2 = 1 - \frac{||M - W \cdot C||_F^2}{||M||_F^2}, \quad (2)$$

which evaluates how well the variability of dance motions was reconstructed by a limited number of motor synergies.

RESULTS: The ten pop dance choreographies' reconstruction levels are depicted in Figure 1. With 10 synergies, all choreographies reached the reconstruction level of 80%. The four modular motor synergies of ten pop dance choreographies are depicted in Figure 2. Ten key movement frames for each choreography, extracted by DeepLabCut (Mathis et al., 2018) with the K-means algorithm, are shown in Figure 3.

DISCUSSION: The reconstruction levels shown in Figure 1 represent the complexity of pop dance movements. The first synergies could only account for the 20% ~ 70% variability of every choreography. This differs from the cases of simple motions such as balance, walking, and sit-to-stand, where about 90% motion variability can usually be accounted for by one synergy. Even with the first two synergies, less than 80% variability was explained. This indicates the complexity of pop dance motions. With the increase of reconstruction level between choreographies, the motion complexity is regarded as being decreased. For instance, body wave, flex and fresno achieved a relatively high reconstruction level even with one synergy, indicating their relatively lower complexity. In contrast, choreographies such as walk, walk out, old man and roll needed about 4-5 synergies to reach the same degree of reconstruction level, indicating their higher complexity.

The modular motor synergies shown in Figure 2 are applied to analyze the motor coordination and joint contributions of pop dance movements. As readily seen, the elbow joints highly contribute to the dance performance, and the strong motor coordination among elbow and shoulder joints can be observed in all the choreographies from the motor synergies W_1 in Figure 2 (a). This indicates a type of motion consistency among different pop dance choreographies. Inshoulder and shoulder joints also display strong motor coordination except for body wave and flex. The hip and knee joints coordinate in the first three choreographies (fresno, walk out, and loft) and the last three choreographies (walk, old man, and roll), while there is no apparent motor coordination among hip and knee joints in the middle four choreographies (hand wave, body wave, neck-o-flex, and flex). These motor coordination and joint contributions can be associated with the key motion frames depicted in Figure 3. As we can observe from the corresponding key motion frames, the middle four choreographies basically are performed with upper body joints. The coordination between the head and neck can also be confirmed in loft and neck-o-flex. The motion contributions of ankle joints are smaller than those of knee and hip joints in all pop dance choreographies.

The second motor synergies W_2 in Figure 2 (b) exhibited similar patterns to those of W_1. The motor coordination and joint contributions of the elbow, shoulder, inshoulder, hip, knee, neck, and head can also be confirmed. The shoulder joints show more significant motion contributions than the elbow in fresno and flex. Motor coordination of hip and knee joints appears in body wave, and flex, which were not observed in W_1. The neck joints display the most significant motion contributions and are firmly coordinated with head joints in the second synergy patterns of neck-o-flex.

The third and fourth synergies represent specific motion patterns shown in Figure 2 (c) and (d), respectively. The motion contribution of the hip, knee, shoulder, inshoulder, and elbow joints can be observed. The significant motion contributions and strong motor coordination of head and neck exist in the third motor synergies of hand wave, flex, and roll, which cannot be observed in W_1 and W_2. The shoulder and inshoulder synergy patterns W_3 and W_4 in hand wave show the largest motion contribution and strongest coordination. The knee joints show the largest motion contributions in W_3 of old man. The most significant motion contributions of knee joints are extracted in W_4 of neck-o-flex, walk, and old man. From the above analysis, pop dance is seen as a type of whole-body motion for which coordination among elbow, shoulder, knee, and hip joints play the main roles in motion performance.

CONCLUSION: The modular motor synergy patterns computed by PCA were used to analyze the motion complexity, joint contributions, motion consistency, and motor coordination patterns of ten typical pop dance choreographies. The commonly recruited body joints of pop dance were those of elbow, shoulder, inshoulder, hip, and knee. The specific head and neck performance are designed for balance maintenance and smooth motion representation. As demonstrated here on the specific dance type (i.e. pop dance), dance synergy analysis helps systematic understanding of dance choreographies and may contribute to the motor coordination study of complex motions as well as dance classification, with potential future applications to choreography design and injury avoidance.

REFERENCES

Ojofeitimi, S., Bronner, S., & Woo, H. (2012). Injury incidence in hip hop dance. *Scandinavian journal of medicine & science in sports*, *22*(3), 347-355.

Labuguen, R. T., Negrete, S. B., Kogami, T., Ingco, W. E. M., & Shibata, T. (2020). Performance Evaluation of Markerless 3D Skeleton Pose Estimates with Pop Dance Motion Sequence. *2020 Joint 9th ICIE) and 2020 4th icIVPR* (pp. 1-7). IEEE.

Bronner, S., & Shippen, J. (2015). Biomechanical metrics of aesthetic perception in dance. *Experimental brain research*, *233*(12), 3565-3581.

Toiviainen, P., Luck, G., & Thompson, M. R. (2010). Embodied meter: hierarchical eigenmodes in music-induced movement. *Music Perception*, *28*(1), 59-70.

Toiviainen, P., & Carlson, E. (2022). Embodied Meter Revisited: Entrainment, Musical Content, and Genre in Music-Induced Movement. *Music Perception: An Interdisciplinary Journal*, *39*(3), 249-267.

Tsuchida, S., Fukayama, S., Hamasaki, M., & Goto, M. (2019). AIST Dance Video Database: Multi-Genre, Multi-Dancer, and Multi-Camera Database for Dance Information Processing. *ISMIR* (Vol. 1, No. 5, p. 6).

Li, R., Yang, S., Ross, D. A., & Kanazawa, A. (2021). Ai choreographer: Music conditioned 3d dance generation with aist++. *ICCV* (pp. 13401-13412).

McFee, B., Raffel, C., Liang, D., Ellis, D. P., McVicar, M., Battenberg, E., & Nieto, O. (2015). librosa: Audio and music signal analysis in python. *14th python in science conference* (Vol. 8, pp. 18-25).

Mathis, A., Mamidanna, P., Cury, K. M., Abe, T., Murthy, V. N., Mathis, M. W., & Bethge, M. (2018). DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. *Nature neuroscience*, *21*(9), 1281-1289.

ACKNOWLEDGEMENTS: This work was supported by New Energy and Industrial Technology Development Organization (NEDO) project JPNP20006, and JSPS KAKENHI Grant Number JP22K20519, Japan.