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Research Article

Evaluation for the Synchronization of the Parade with OpenPose

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ABSTRACT

In military organization, the synchronization in the parade is important for showing their majesty. However, we do not have any quantitative evaluation methods for the parade. In this research, as a first step of the quantitative evaluation for the parade, we propose an evaluation method focusing on the synchronization level of "Marking Time", in which soldiers is moving their legs as in marching without step forward, between two persons with OpenPose. In order to measure the synchronization level, our method is based on the trend of the transition of arm swing angles in the parade, and the result shows our method is appreciable for measuring the synchronization level for two persons.

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1. INTRODUCTION

In the military parade, the synchronization is a major factor for the performance. Shimohagi, Ishihara, and Okugawa [1–3] conducted scientific analysis for the synchronization of the parade; however, it is difficult to measure the synchronization level of the parade because it requires a large number of posture data at same time. We do not have any quantitative evaluation methods for the synchronization level of the parade. In this research, we propose the evaluation method for the synchronization level with OpenPose. OpenPose [4] can measure many kinds of postures from images simultaneously, therefore, it is much easier to get a large number of posture data than conventional motion analysis with motion capture [5,6], and it is suitable for analyzing cooperative operation of multiple people such as parade (Figure 1).

As a first step of this research, for measuring the synchronization level of the whole of the parade, we focus on the arm swing of two persons in "Marking Time". Marking Time is a kind of parade style, in which soldiers is moving their legs as in marching without step forward. In this paper, we analyze the synchronization level of the marking time, between two persons with OpenPose. When we evaluate the synchronization level of the two persons appropriately, we can evaluate the synchronization level of the parade.

This paper is organized as follows. After introducing OpenPose in the next section, we describe the data processing method with OpenPose. In Section 4, we propose the evaluation method for the synchronization level. After explaining the two experiments with 3D CG and real behavior of the marking time by two persons, we

show our results from the experiments. In addition, this paper is updated with the results of reviews from the proceeding paper in ICAROB [7].

2. OPENPOSE

OpenPose represents simultaneous posture recognition of multiple people on single images. The left side of Figure 2 shows an example of pose estimation with OpenPose. If the movements of the two are synchronized, we can expect that we get the same trend data.

The right side of Figure 2 shows the points of posture data.

As the three-dimensional data of [x, y], likelihood] on each point, we can obtain 75 data for one piece of posture information. It is difficult to measure the synchronization because the values and the accuracy of the posture data are different depending on the position and body size. Therefore, it is necessary to use the trend of data which is not influenced by position or height as an index. We can get the posture data of each person in same frame with OpenPose, but the data is not related to the posture data in the before and the after frames. In order to obtain the time series posture data of each person, we did cluster analysis based on the location in each frame.

3. PROPOSED METHOD

In this section, we propose the measurement method using indicators focusing on inflection point of movement. In the following, we explain the proposed method in order.



Figure 1 | Military Parade with OpenPose (https://www.youtube.com/watch?v=zaviumhF7aA).

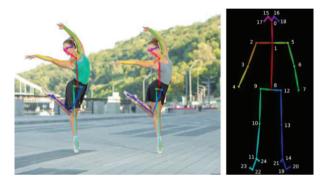


Figure 2 | Multi-person pose estimation with OpenPose.

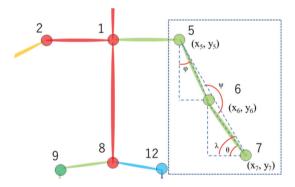


Figure 3 | Focus points of OpenPose.

3.1. Focus Points

Focusing on the synchronized arm swing of the left hand, we obtain the data of each shoulder (point 5 in Figure 3), elbow (point 6 in Figure 3) and palm (point 7 in Figure 3). Each data, which are points 5–7, are one-unit set. After we get time series data of each member, we converted the data into four angles: φ , ψ , λ , θ (Figure 3).

3.2. K-means Clustering

In order to get time series data of each person's arm swing angle in the image, we conduct the clustering using K-means clustering [Equation (1)]. We use K-means clustering to the data of shoulder (point 5 in Figure 3), Given a set of data $(x_{5_{tramel}}, x_{5_{frame2}}, x_{5_{frame2}}, \dots, x_{5_{framen}})$,

K-means clustering aims to partition the *n* observations into *k* sets $S = \{S_1, S_2\}$, where μ_i is the mean of points in S_i and $Var(S_i)$ is squared deviation of S_i .

In this section, we analyze the marking time movies to get time series data of each two persons, therefore, we set K = 2 for the cluster analysis using K-means method.

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_{i}} ||x - \mu_{i}||^{2} = \arg\min_{S} \sum_{i=1}^{k} |S_{i}| \operatorname{Var}(S_{i})$$
 (1)

3.3. Smoothing

In order to read the inflection point of the time series data of arm swing angle accurately, we use Simple moving average [Equation (2)] for smoothing out short-term fluctuations of the angle data. Simple moving average is the unweighted mean of the n data. When we have a series of the angle data (Ang, Ang, ..., Ang, ..., Ang, then the simple moving average Ang, is

$$Ang_{sma} = \frac{Ang_t + Ang_{t+1} + \dots + Ang_{t+n}}{n}$$
 (2)

In this method, we set n = 8 for reading the inflection points accurately.

Figure 4 shows an outline of the data before and after the smoothing process. It can be seen that the outline is smooth, and the inflection points are easy to read.

3.4. Evaluation

After smoothing out, we get the time series data of arm swing angle [Equation (3)].

$$\vec{A} = [\text{Ang}_{A1}, \text{Ang}_{A2}, \dots, \text{Ang}_{Ai}]$$
 (3)

 \vec{A} is the time series data of arm swing angle of member A in an image, and Ang_{A1} is the arm swing angle of member A at the first frame of the movie.

From each time series data of the arm swing angle, we use correlation coefficients for evaluation. We define the synchronization level r as follow [Equation (4)]:

$$r = \frac{\sum_{i=1}^{n} (\text{Ang}_{Ai} - \overline{\text{Ang}_{A}})(\text{Ang}_{Bi} - \overline{\text{Ang}_{B}})}{\left(\left(\sum_{i=1}^{n} (\text{Ang}_{Ai} - \overline{\text{Ang}_{A}})^{2}\right)\left(\sum_{i=1}^{n} (\text{Ang}_{Bi} - \overline{\text{Ang}_{B}})^{2}\right)\right)^{\frac{1}{2}}}$$
(4)

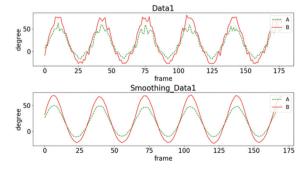


Figure 4 Data smoothing before and after.

We use Pearson's moment correlation coefficient <u>as the synchronization</u> level. When we have the arithmetic mean \overline{Ang}_A and \overline{Ang}_B , which is from the data \vec{A} and \vec{B} , the synchronization level r is expressed as [Equation (4)]. If r approaches 1, it is synchronized. If r approaches -1, it is expected that the phase will be in opposite.

4. EXPERIMENT

In this chapter, we conducted two kinds of experiments. In Experiment 1, we examined the measurement accuracy and the evaluation index of our method using 3D CG models. After confirming the effectiveness of the evaluation method, in Experiment 2, we evaluate the synchronization level r in real marking time behavior with our method.

4.1. Experiment 1: Accuracy of Our Method

For measuring the effectiveness of our method, we analyzed the 3D CG models created by Unity. Since we can adjust the synchronization level between two models, it can be an ideal analysis target. 3D CG is appropriate for evaluating the synchronization level of the parade because we can completely control human-like model.

In the 3D CG, the two models are only doing the marking time (Figure 5).

The arm swing angle of the 3D CG models was implemented according to the simple vibration [Equation (5)]. In this section, the phase difference of the arm swing angle is expressed by changing the initial condition of θ_0 as 0, $\pi/8$, $\pi/4$, $\pi/2$ and π .

$$x = A\sin(\omega t + \theta_0) \qquad (\omega = 2\pi)$$
 (5)

Figure 6 shows the synchronization level r of time series angle data of two models with four different angles. Each angle is represented different figure such as φ is represented as square. As the initial value θ_-0 shifts from 0 to π , the value r decreases in four angles. Also, when the initial value θ_-0 is π , that is, each arm swing angle is in opposite phase, it approaches -1 in four angles. The synchronization level of four angles are almost same in Figure 6.

From the result, the synchronization level r is monotonically decreasing according to the value θ_0 . Therefore, it was confirmed that our evaluation method is appreciable for measuring the synchronization level in the 3D CG marking time movie.



Figure 5 An example of 3D CG models with OpenPose.

4.2. Experiment 2: Evaluation of Marking Time

Since we can show our evaluation method is appreciable, we evaluated the synchronization of the real marking time. As in Experiment 1, we analyzed the marking time of two persons. We experimented with 6 pairs of two cadets in the National Defense Academy, which have parade training every day (Figure 7).

For Experiment 2, we have three types of arm swing: *Phase Synchronization*, *Phase Difference* and *Phase Opposition*. Figure 7 shows a snapshot of *Phase Opposition*. Both cadet arm swing is opposite in Figure 7.

Figure 8 shows the average of the synchronization level r of marking time. As shown in Figure 8, we can confirm that the synchronization level r decreases as the difference of the arm swing angle shifts.

Figure 9 shows the synchronization level r in each angle with standard deviation. In *Phase Difference* case, we did not set the different level of the arm swing quantitatively like as Experiment 1. Therefore, the standard deviation of Phase Difference is wider than

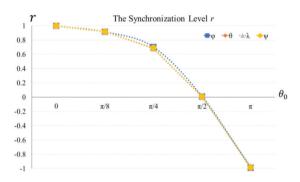


Figure 6 The synchronization level *r* of 3D CG.



Figure 7 A capture of real marking time with OpenPose.

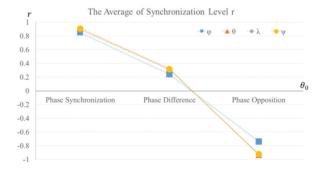


Figure 8 The synchronization level *r* of marking time.

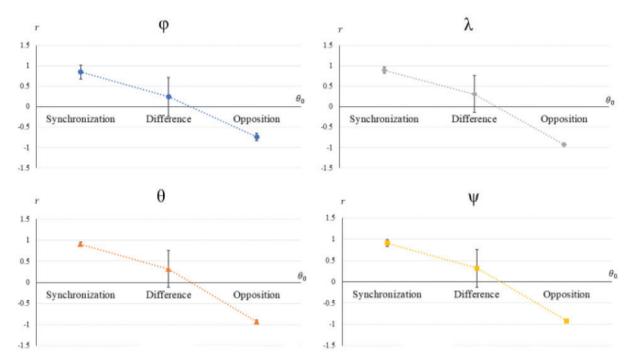


Figure 9 The synchronization level *r* in each angle with standard deviation.

other cases. However, the results of Experiment 2 show the same trend as the result of Experiment 1, and it is our evaluation method is appreciable for measuring the synchronization level in the real Parade. In addition, it was suggested that measuring the synchronization level with armpit angle (φ) has good sensitivity for evaluation comparing to other angles.

5. CONCLUSION

We propose the evaluation method for the synchronization level of the marking time with OpenPose. We focus on the arm swing angle and analyze the marking time for two persons. Through the experiment using 3D CG, it was confirmed that our method based on time series arm swing angle is appreciable for measuring the synchronization level. Moreover, through the experiment of real marking time of six pairs of two cadets, our evaluation method is appreciable for real environment. In addition, it was suggested that measuring the synchronization level with armpit angle has good sensitivity for evaluation.

REFERENCES

[1] T. Shimohagi, Parade analysis based on network system, Proceedings of National Defense Academy of Japan Graduation Thesis, 2017, pp. 61–62 (in Japanese).

- [2] T. Ishihara, Development of VR parade training system, Proceedings of National Defense Academy of Japan Graduation Thesis, 2018, pp. 47–48 (in Japanese).
- [3] Y. Okugawa, M. Kubo, T. Shimohagi, T. Ishihara, H. Sato, Analysis of a parade with the Kuramoto model -for better performance without trainings-, Proceedings of IEEE SMC, IEEE, Miyazaki, Japan, 2018, pp. 4005–4010.
- [4] Z. Cao, T. Simon, S.E. Wei, Y. Sheikh, Realtime multi-person 2D pose estimation using part affinity fields, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Honolulu, HI, USA, 2017, pp. 1302–1310.
- [5] K. Inada, T. Ishikawa, H. Watanabe, Coincidence evaluation of multiple people's dance using OpenPose, Proceedings of the 80th National Convention of IPSJ, IPSJ, Tokyo, Japan, 2018, pp. 257–258.
- [6] M. Nakai, Y. Tsunoda, H. Hayashi, H. Murakoshi, Prediction of basketball free throw scoring by OpenPose, Prediction of Basketball Free Throw Shooting by OpenPose, New Frontiers in Artificial Intelligence JSAI-isAI 2018 Lecture Notes in Computer Science, vol 11717, Springer, Cham, 2018, pp. 435–446.
- [7] Y. Okugawa, M. Kubo, H. Sato, B.D. Viet, Evaluation for the synchronization of the Parade with OpenPose, Proceedings of the 2019 International Conference on Artificial Life and Robotics (ICAROB), Oita, Japan, 2019, pp. 443–446.

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