# Motion Causal Network Analysis for Quantitative Evaluation of Baseball Form by Video Analysis

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Abstract:     In professional sports, IT technology has been introduced to strengthen players, and in the baseball industry, where there is a large number of athletes, data analysis is expected to improve training efficiency, even for amateurs. However, the use of IT has not been widespread in the past due to the need for special equipment for measurement and the difficulty of interpreting data. In this study, we proposed a technique for quantifying the interlocking nature of players' forms using the transfer entropy from time-series data of players' skeletal coordinates obtained by image recognition to intuitively visualize the characteristics of players' forms using only video. As a result of evaluating players' hitting form using the proposed technique, we confirmed that the transfer entropy significantly changed in the target region when players were conscious of improvement, and we obtained a prospect for the practical application of form analysis using video.

## 1 INTRODUCTION

Wearable devices, camera-based measurement technology, and AI-based analysis technology are rapidly being applied to sports. Major professional sports teams such as soccer and baseball use data for player evaluation, performance improvement, and injury prevention. Data measurement and analysis technologies developed in professional sports are expected to spread to amateur sports teams and players.

In baseball, which has long been a popular sport in Japan, detailed scores and notes have been manually recorded throughout professional and amateur sports for use in competition and coaching, and data measurement devices have been used in amateur coaching from early on. Developed from speed guns that use ultrasonic waves to measure the velocity of pitches and batted balls, devices that record not only velocity but also trajectory and rotation in detail have become popular in professional stadiums, and products for amateur teams are also on the market. In addition, devices with acceleration and gyro sensors mounted on bats and balls are also available, enabling simple visualization and analysis of pitching velocities and swing trajectories in individual practice. In recent years, it has become possible to take pictures of pitching and hitting forms with a smartphone without using special equipment, and the AI automatically recognizes joint angles and skeletal positions from the images, converting them into data for visualization (Chung, 2022).

However, the problem is that only a limited number of teams and players are able to use this technology because professional-grade measuring equipment is expensive and requires human resources to operate, and instructors with specialized knowledge are needed to interpret the data and provide guidance. Because of the high cost of ultrasonic equipment, only top-level amateur players belonging to famous teams can use it, and the disparity in coaching has also been a factor hindering the development of amateur baseball. In addition, although measurement by smartphone is relatively inexpensive, it has been limited to measurement of the skeletal position, so interpretation of data has been limited to a few instructors, making it difficult to spread the use of smartphones among a wide range of levels and generations of amateur baseball players.

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In this study, we aim to enable amateur athletes to easily measure their own condition, convert it into data, and practice PDCA in training based on the accumulated data of analysis subjects and others by visualizing the characteristics of pitching and hitting form movements from videos taken with a smartphone in an easy-to-understand manner. We propose a "motion causal network analysis technology" that visualizes the characteristics of pitching and hitting form movements from videos taken with smartphones in an easy-to-understand manner. A method has been developed to estimate the linkage of group movements in soccer and other sports using transfer entropy and to visualize the relationships among groups in a network (Itoda, 2015). In this study, we apply the method to analyze a group and visualize the linkage by considering each part of an individual's form as a group. In this paper, we report on a prototype system that visualizes the results of applying causal network analysis of movements by inputting videos taken with a smartphone and evaluate whether the system can visualize the effects of the practice intended by the individual using data from actual amateur athletes.
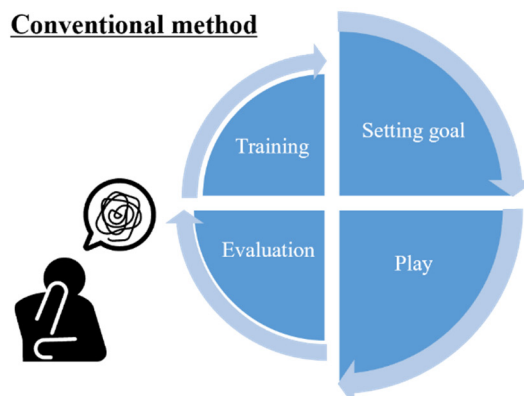
## 2 METHOD

### 2.1 Baseball Training Using Digital Technology

This study aims to provide amateur baseball players with a wide range of environments for data utilization so that they can think and practice how to grow by themselves. In baseball, it is common practice for players to record their findings in a notebook and repeat trial and error in the process of training and receiving instruction. In recent years, with the spread of smartphones and the Internet, methods to record and check one's own form on video and to compare one's own form with that of model players, such as professionals using video-sharing services, are widely used. In light of these current conditions, our research aims to promote the utilization of knowledge by digitizing amateur players' baseball notebooks and to create a collaborative environment by sharing the notebooks with others in the future. Furthermore, it is desirable to be able to provide new insights that could not be obtained only by the player's subjective view by using AI to analyze videos of his or her form, quantifying and visualizing his or her past and differences from others in an easy-to-understand manner. By providing these functions as a web system that can be used only with a smartphone, we

aim to provide more growth opportunities to amateur athletes who have not had access to state-of-the-art equipment or a coaching environment.
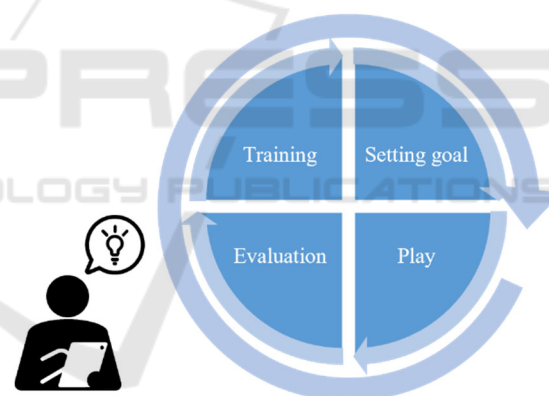


Figure 1: The effect of our aimed training with digital technology.

### 2.2 Body Tracking from Images

With the development of image analysis technology using deep learning, it has become possible to detect people from images with high accuracy. In recent years, various skeletal points such as hands, feet, and face can be recognized and output as coordinates. Furthermore, several OSS libraries, such as OpenPose (Qiao, 2017), have been released, making it possible to easily implement skeletal recognition functions from images into applications. Many

libraries support the output of 2D skeletal coordinates, but libraries that estimate 3D coordinates are also beginning to be provided. However, the accuracy is currently low, and it is intended for entertainment applications such as VR, so it is not suitable for use as measurement data. In this study, we applied trt_pose provided by Nvidia, considering its licensing and ease of implementation, etc. The coordinate points of the skeleton that can be recognized by trt_pose are shown in Figure 2 and Table 2. The trt_pose can recognize 18 joint points defined in the MSCoCo dataset (Janardhanan, 2022). In this study, since the baseball form is the target, facial points are not necessary, and only the nose is treated as the head, and the 14 points other than the facial points are mainly used.

Table 1: Recognized joint points.

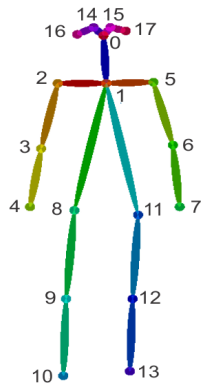| ID | Joint name |
|----|------------|
| 0 | Nose |
| 1 | Neck |
| 2 | Right shoulder |
| 3 | Right elbow |
| 4 | Right wrist |
| 5 | Left shoulder |
| 6 | Left elbow |
| 7 | Left wrist |
| 8 | Right hip |
| 9 | Right knee |
| 10 | Right ankle |
| 11 | Left hip |
| 12 | Left knee |
| 13 | Left ankle |
| 14 | Right eye |
| 15 | Left eye |
| 16 | Right ear |
| 17 | Left ear |

Figure 2: Coordinates of joint points.

## 2.3 Motion Causal Network Analysis Techniques

Using time series data of joint point coordinates extracted from videos of pitching and hitting form, we propose a motion network analysis technique to visualize the linkage of motion between each skeletal point in order to quantify and visualize the characteristics of skeletal motion. This technique is based on the technique for quantifying and visualizing the linkage between players in group sports. This technique uses transfer entropy (Staniek, 2008), quantifying the strength of the dependency between two time-series data considering causality by information theory. These include nonlinear analytical methods that use mutual information content, relative entropy, etc. Although these methods are suitable for evaluating the strength of the relationship between two signals, they are not suitable for analyzing the direction of information flow, i.e., causality, because they are symmetrical with respect to the two signals. In contrast, the application of transfer entropy has recently been promoted as a method suitable for causality estimation. It has been used in research to estimate neurotransmission from time series signals showing the activity of each neuron in brain measurement, which is also a field of human measurement (Wibral, 2014), and in research such as communication analysis in human infants (Hidaka, 2013), and it has been found that transfer entropy can be applied even between signals with nonlinear fluctuations. It has been found that the transfer entropy can be applied between signals that vary nonlinearly.

Figure 3 shows the process flow for calculating the transfer entropy between two skeletal coordinates and visualizing the entire skeletal network. First, in process (1), skeletal coordinates are extracted from the image of each frame of the video, time series data of the coordinates of each skeletal point is generated, and the amount of movement per second is calculated from the time series data of the coordinates. In process (2), the time-series data of the variable (amount of movement) for each skeletal point is transformed into a discrete random variable that is normalized based on the histogram of the intensity of movement of each skeletal point. In other words, they are transformed into discrete states discretized by the intensity of the movement. The number of divisions k of the histogram was determined based on the Sturges formula. l is the number of data in the time series data of the variable. The amount of information transfer between the variables of the two players is calculated from the transfer entropy in the process (3). Here, if

the elements of the random variables I and J at time step n are $i_n$ and $j_n$, the transfer entropy $T(J \rightarrow I)$, which indicates the influence of J on I, is calculated by the formula in Figure 3, where $P(i_{n+1}, i_n, j_n)$ is the simultaneous probability of $i_{n+1}$, $i_n$ and $j_n$, and $P(i_{n+1}|i_n)$ denotes the conditional probability of being $i_{n+1}$ when $i_n$. Given two time-series data, I and J, we can measure the degree of uncertainty that changes relative to the uncertainty of predicting J's next state from I's past series when we add J's past series The transfer entropy is a measure of the degree of uncertainty in the future state of J. The transfer entropy takes values between 0 and 1; with larger values, the more causally related I and J are. In this study, since the time series data of joint point coordinates extracted from the video was used, the effect of the amount of movement of J on the amount of movement of I in the next frame was calculated.
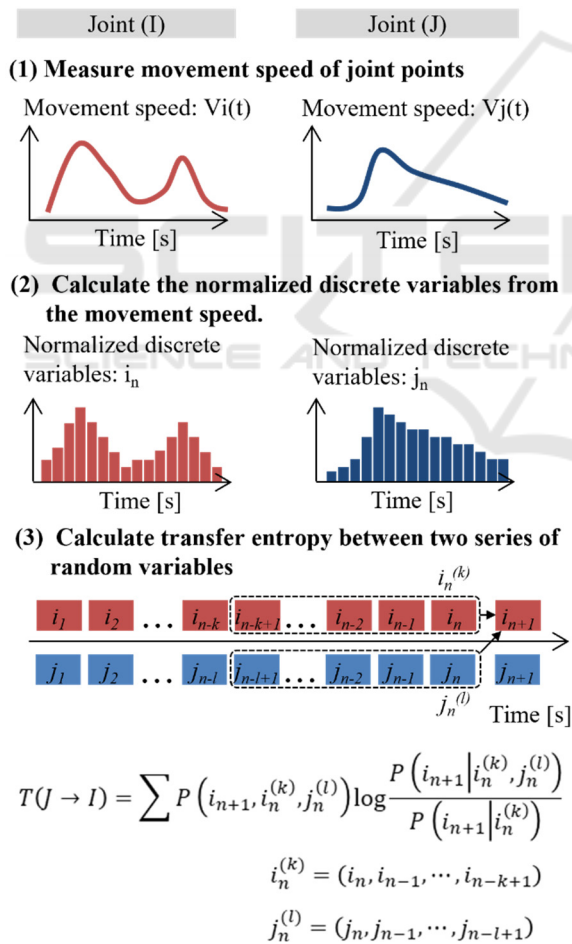


Figure 3: Processing flow of transfer entropy calculation.

In order to draw a network from the calculated transfer entropy, the transfer entropy of all the paths

of two points from all the skeletal points is calculated, and a directed graph is drawn by considering that there is a linkage above a certain threshold value. The number of graph occurrences can be adjusted by adjusting the threshold value. The directed graph data can be subjected to various network analyses, such as centrality and page rank, allowing quantitative analysis of network characteristics.
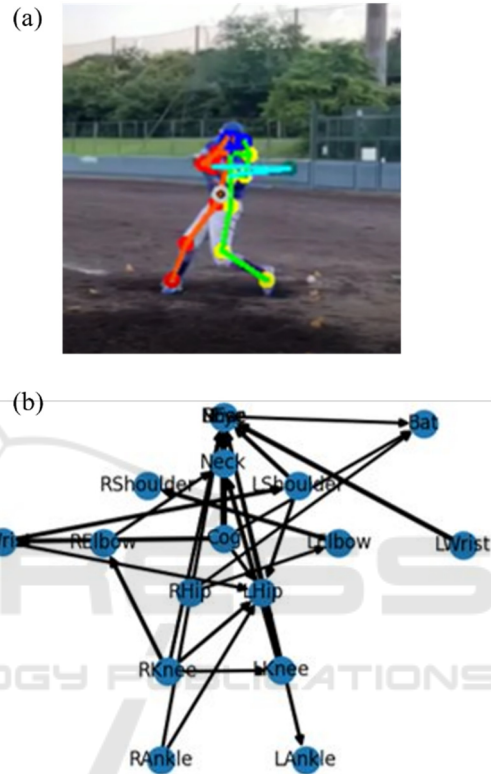


Figure 4: Visualization of causal network analysis.

Table 2: Definition of metadata.

| Input item | Contents |
|---|---|
| Type of ball | Hardball/ softball/ urethane/ sand/ other |
| Type of bat | Material, length, weight |
| Condition of the ground | Soil/ grass/ concrete/ mats |
| Type of shoes | Athletic shoes/ spikes/ others |
| Weather | Sunny/cloudy/rainy/snowy, temperature, wind speed (tailwind/ head wind/ cross wind) |
| Date and time | yyyy/MM/dd HH:mm:ss |
| Comment | free |

## 2.4 Development of Prototype System

As a prototype system for this study, we constructed a web system that allows users to upload videos of their forms from their smartphones and visualize the output results of motion network analysis. When a user analyzes his/her form, he/she first prepares a video of his/her form. If the form is a hitting form, the user prepares a video of only one swing, trimmed in advance using a smartphone function or the like. When uploading the video, the conditions under which the form was taken can be entered as metadata. The input items are defined as shown in Table 3, referring to the items noted in a typical baseball notebook. The analysis results of each video can be retrieved by using each item of metadata as a key, so it is possible to compare the differences in form between videos under various conditions or to compare the changes before and after practice by specifying the date and time. Figure 4 shows an example of the results of applying motion network analysis. In addition to the coordinates based on skeletal recognition, the prototype system we developed estimates the position of the center of gravity, which is generally considered important in form evaluation, and adds it to the joint point coordinates. Furthermore, the tip of the bat used in baseball hitting can be recognized by image processing and added as one of the skeletal coordinates, enabling evaluation of the direct effect of body usage on the swing.

## 3 EVALUATION

To evaluate the validity and usefulness of the results of motion network analysis using the proto-system, we input videos of actual baseball hitting practice forms and compared the results of transfer entropy calculation with subjective evaluation. The subject was a player belonging to a baseball team for working people. 10 videos of each of the two patterns of hitting (A and B) shown in Figure 5 were filmed and analyzed. Pattern B is the hitting form of tee-batting with a fixed ball, in which the subject player works on improving his hitting form. We interviewed the players about the points of improvement they were aware of in Patterns A and B, and summarized the correspondence with the hypotheses quantitatively evaluated by motion network analysis in Table 4. Improvement point (1) is related to the difference between hitting a tossed ball and hitting a placed ball. In placed tee batting, the player hits a fixed ball, which stabilizes the form. Therefore, B is considered

to have less variation than A in the transfer entropy of the motion network analysis. Improvement point (2) is that in A, the player tries to hit the ball far away and puts unnecessary force on the lower body, whereas in B, the player is conscious of the stability of the lower body. Therefore, it is thought that the variation of the lower body value and the influence on other parts of the body are reduced in the transfer entropy. Point (3) is the use of the elbow and wrist in the upper body. in order to improve the situation in A, where the bat swing lags behind the body rotation (commonly called the state where the upper body is open), in B, the right elbow to the armpit is slightly opened, and the upper body is rotated together with the left shoulder to left elbow rotation, which results in a more delayed right elbow and wrist rotation. As a result, he is more conscious of delaying the external rotation of the right elbow and wrist and rotating the upper body (reducing the openness of the upper body). Therefore, in the transfer entropy, there is a linkage from the left elbow to the right elbow and wrist. We quantitatively and statistically evaluated whether the results of the movement network analysis were valid for the hypotheses at these points of awareness.

Table 3: Key points of improvement and hypothesis of data analysis.

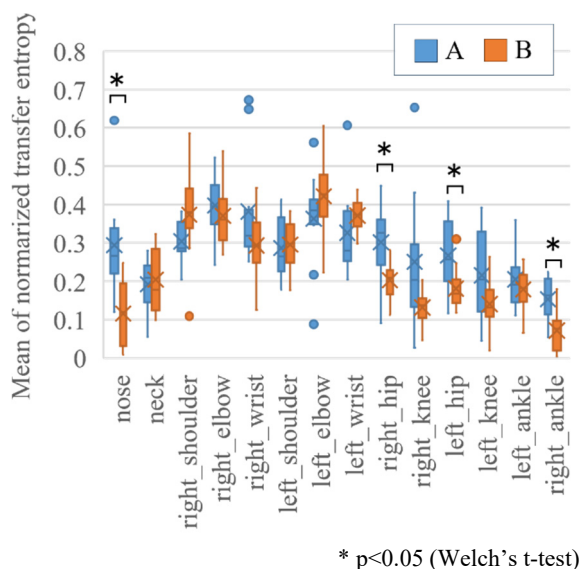| No. | Key Points of Improvement | Hypothesis of data analysis |
|---|---|---|
| 1 | B is more stable because the ball is fixed. | The variation of transfer entropy in B is smaller than in A. |
| 2 | B is more aware of lower body stability. | The transfer entropy starting from some lower body point decreases. |
| 3 | In B, the right elbow to the side is slightly open, and the right elbow and wrist are delayed in rotation. | Transfer entropy from the left elbow to the right elbow and wrist tends to be higher. |

(A)        (B)



* p<0.05 (Welch's t-test)

Figure 6: Mean of the transfer entropy starting at each joint.
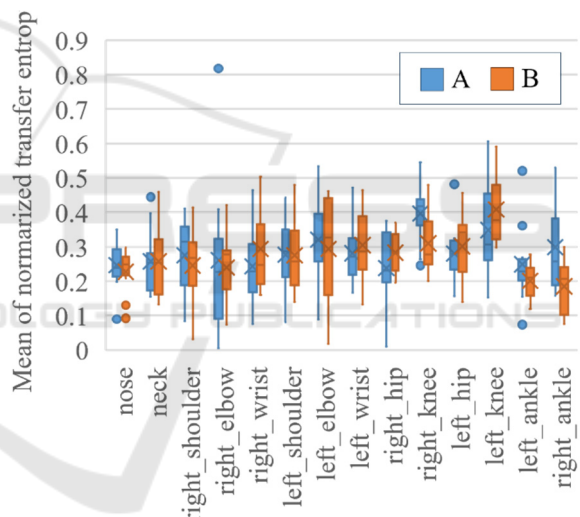


Figure 7: Mean of the transfer entropy toward each joint.

## 4 RESULT

### 4.1 Improvement Points (1) and (2)

To evaluate improvement point (1), we compiled the transfer entropy for each swing of A and B and compared the mean value of transfer entropy where each site is the starting point with the mean value of transfer entropy where each site is the ending point, as shown in Figures 6 and 7. To test the hypothesis of improvement point (1), Table 5 summarizes the standard deviations of the values for each site, and as

Figure 5: Sequential images of the evaluated batting forms.

(A) Toss batting with normal awareness (B) Tee batting with awareness of points for improvement.

shown in Figures 6 and 7, A has many outliers and a large variation in values. The standard deviation values in Table 5 are also significantly lower for B for the transfer entropy at the starting point. On the other hand, a decreasing trend was observed for B for the endpoint transfer entropy, although it was not significant. In other words, the results are in accordance with the hypothesis that B has less variation in the evaluation using the transfer entropy.

To evaluate the improvement point (2), a t-test (Welch's t-test) was performed for each site to compare the distribution of the transfer entropy of the starting point of each site, as shown in Figure 6. The significance level was set at 0.05. The results showed that the mean value of B, which is the starting point, decreased in the left and right hip, knee, and ankle, which are the lower body regions, and that there was a significant decrease, especially in the right_hip, left_hip, and right_ankle. This result is in accordance with the hypothesis that the lower body's extra movement decreases due to the awareness of lower body stability and that the transfer entropy as the starting point decreases. In addition, there was also a significant decrease in the starting point of transfer entropy at the nose, which is the head, indicating that not only the lower half of the body but also the upper half of the body showed a decrease in extra movement.
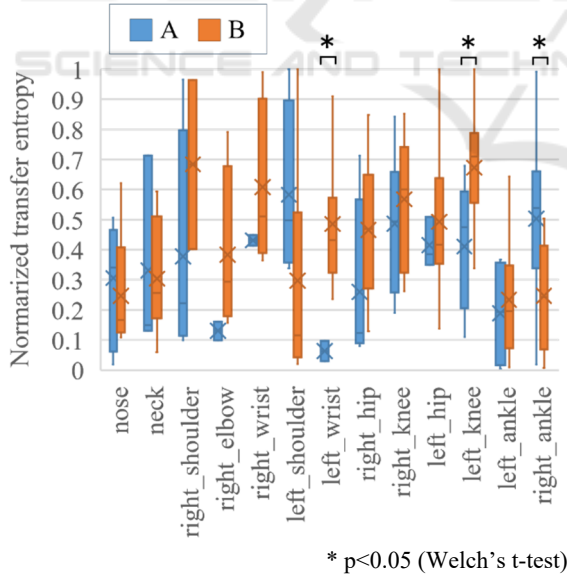


* p<0.05 (Welch's t-test)

Figure 8: Mean of transfer entropy from left_elbow to each joint.

## 4.2 Improvement Points (3)

To evaluate the improvement point (3), we compared the transfer entropy for each site starting from left_elbow as shown in Figure 8. The results showed that the transfer entropy increased significantly in B for the left_wrist, right_wrist, and right_elbow, which are related to the improvement point (3). As a result, less than 5 out of 10 swings were calculated correctly, which was insufficient for statistical evaluation. In addition, there was a significant increase in transfer entropy for the left_knee and a significant decrease for the right_ankle, which were not included in the hypothesis for improvement point (3). Although these results were not included in the players' awareness, improvement points (2) and (3) resulted in increased rotation of the upper body and knee regions.

## 5 DISCUSSION

The validity of the results of this report was examined based on interviews with the players and teams included in this study. In the motion network analysis of form A→B, which the players consciously aimed to improve, reasonable results close to the hypothesis were obtained for improvement points (1), (2), and (3). For improvement point (1), outliers were reduced at B in the transfer entropy of the start and end points, and the variability was reduced. On the other hand, the significant decrease only at the starting point may be because the end point is less stable than the starting point, which is a characteristic of the subject athletes. In the improvement point (2), a significant decrease was observed, especially in the hip near the waist, which may be because the knee has large movement and is prone to recognition errors. Further verification of the difference in awareness of the knees and hips in the form is needed. In the improvement point (3), the linkage between the left_elbow and other wrists and elbows changed as hypothesized. However, the skeletal structure of the right hemisphere, which is hidden during the swing, was difficult to recognize from the photographer's side, and this did not lead to sufficient verification. In this respect, improvements are needed, such as in the shooting method and in the use of skeletal recognition libraries that are relatively accurate even for the hidden parts.

The usefulness of this technology was also examined in the same way. We presented the linkage of each part visualized in the motion network analysis to the players and obtained an evaluation that it was intuitively easy to understand. This is useful for confirming the points that players were conscious of in practice, including the validity of the hypothesis. In addition, the metadata collected simultaneously was also evaluated as having the necessary information for form evaluation based on interviews

with players and teams. On the other hand, there are many points in the motion network analysis where it is difficult to understand the network formation by transfer entropy, except in the hypothesized areas. In the future, it will be necessary to collect more data on more forms and to increase the number of patterns in interpreting the meaning of the starting and ending points of the transfer entropy through repeated verification of the hypothesis. Since only two patterns of forms were tested in this report, we did not go as far as to compare data from different environments utilizing metadata or to compare data from other people. Methods and designs to make players aware of the ability to accumulate and share large amounts of data also need to be considered.:

## 6 CONCLUSIONS

We proposed a motion network analysis method that recognizes the positional coordinates of the skeletal structure from videos of athletes taken with smartphones, quantifies the linkage of the movements of each part using transfer entropy, and visualizes the relationship between them to promote effective training methods that utilize data in the amateur sports industry. Furthermore, we developed a prototype system that visualizes characteristic points from videos of baseball forms by motion network analysis and records and stores notes on the environment and situation at the time of filming. In order to evaluate the proposed method and the prototype system, we analyzed videos of one amateur baseball player, taking 10 videos each of tee batting with a normal front toss and the form of a replacement tee batting that he worked on with an awareness of improvement, and formulated a hypothesis for the data regarding the three points of awareness and conducted a statistical evaluation. Statistical evaluation was conducted. The results of the analysis showed significant changes ($p<0.05$) consistent with the hypotheses, including a reduction in the variability of transfer entropy due to stabilization of form and an improvement in wrist and elbow coordination due to changes in the use of the right elbow. This evaluation confirmed that the players themselves intuitively understood the effects and noticed the points that they worked to improve. Based on these results, we conclude that the proposed method can be used to easily identify the characteristics of players' form and may contribute to improving the efficiency of training for a larger number of players through the accumulation of data and hypothesis testing.

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