Visualization of Cognition and Action in the Shooting Skill Acquisition Process in Ice Hockey

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Abstract. To support the process of skill acquisition, a system that visualizes both cognition and action is required. This study aims to build such a system. To this end, this study conducted experiments on slap shot in ice hockey and attempted to visualize cognition and action in the process of acquiring shooting skills. Slap shot is a type of shot performed when a player swings his stick back and then down to strike the puck with maximum force toward the goal. It is the strongest shot in ice hockey. This study conducted 9 identical experiments in about two months. Each experiment consisted of a pre-test, practice, and post-test. The research participant made 15 slap shots in each test. Practice lasted for 10 minutes. The 21-year-old research participant had eight years of experience in ice hockey. The experiments of shooting training were conducted on acrylic boards, rather than on ice, in an experimental laboratory. The research participant wore gloves and used sticks but did not wear skates in the experiments. The experiments were conducted with shooter tutors for ice hockey goals. The research participant was instructed to make a strong shot at the upper right of the goal area by slap shooting. The research participant described his cognition data in the report after the post-test. In the report, the research participant was guided to answer four questions; an example is: To which aspects did you pay attention when you made a strong and accurate slap shot in today's practice? Please describe them in detail as much as possible. This study created a network analysis on the report using "KBDex," which visualizes the process of discussions. Action data were measured and converted into variables using video cameras and motion capturing systems. Then such variables, which described the positions and velocities of body parts, were analyzed. FWDpowershot, an acceleration sensor and ice hockey stick center, presumed and recorded the shooting speeds in the pre- and post-tests. The number of shots that came into the upper right zone was also recorded in the pre- and post-tests. We aimed to clarify further the process of acquiring shooting skills in ice hockey, thereby enabling the building of a visualizing system based on adequate analyses.

keywords: Expertise, Cognition and Action, Visualization, Ice Hockey Shooting

1 Introduction

It is essential to evaluate and support the learning process. The new (2018) version of Japan's curriculum course guidelines (Ministry of Education, Culture, Sports, Science and Technology[1]) stipulates that teachers should focus on the process of learning when evaluating their teaching and designing future lessons. But this presents frontline teachers with a challenge: what methodology should they employ to this end? Educators have for years stressed the importance of evaluating and visually modeling the learning process. However, there is now a plethora of learning applications in use thanks to the rise of information and communications technologies, and it is essential to evaluate how these applications should be used in practical settings. In many learning settings, and in sports skill learning in particular, complex knowledge and skills acquisition occurs tacitly. Accordingly, it is important in such learning settings to visualize the relationship between these two aspects of learning.

To support the process of sport skills acquisition, it is necessary to visualize two processes in the learner—a tacit cognitive change process and a motor skill acquisition process—and then share this information with learners and coaches. Therefore, we sought to visually model the cognitive and biomechanical aspects of sport skills acquisition.

1.1 Visualizing the Learning Process

Strom et al. (2001)[2] developed a graph for visually modeling mathematical argumentation in a second-grade classroom. The graph presents the children's conversation in 10-minute sections, allowing one to see how conceptual knowledge changes over time in the class as a whole. Such a visual model can help educators evaluate the learning process and provide support accordingly. However, this model presents a burden to teachers: they have to transcribe every conversational exchange and manually compose a network chart.

In another study, Zhang et al. (2009)[3]visually modelled students' learning interactions. In a three-year experiment, they analyzed network structures in three classes of fourth graders (taught by the same teacher) and derived teaching strategies from these analyses. Thus, new technology is dramatically changing researchers' analytical techniques and visual modeling.

1.2 Network Analysis

As we see in the works by Barabási (2005)[4] and Strogatz (2001) [5], network analysis is garnering increasing scholarly attention because it allows researchers to analyze and visualize complex social networks. A basic analytical index used in network analysis is "degree centrality," which describes the number of connections in a network (Nieminen, 1973)[6]. Using the principles of network analysis, Matsuzawa (2011)[7] developed a computer application called Knowledge Building Discourse eXplorer (KBDeX). KBDeX analyzes inter-word connections (collocations) in learning discourses. It has already been used in learning settings to analyze learners' discourses. Oshima et al. (2012)[8] used KBDeX to analyze learners' physics group work and found that the assistant teacher's utterances heavily influenced the quality of learners' discourses. Studies such as this demonstrate that KBDeX compares favorably against traditional discourse protocol analysis, and that it is therefore valid as a tool for analyzing discourses.

1.3 Visualizing Motion in Sports

Up to this point, we have cited examples of visually modeling discourse data (such as network analysis). When it comes to supporting sport skills acquisition, however, it is also important to measure and visually model the motions of learners' athletic maneuvers. If educators could visualize learners' key biomechanical actions and then compare them with their past biomechanical actions, they might be better able to support the skill acquisition process. There have been attempts to visualize learners' biomechanics and provide support accordingly. Nishiyama and Suwa (2010)[9], for example, quantitatively measured the biomechanics of learners' baseball swings. They then visualized this biomechanical aspect by, among other things, paring color tones with swing speeds. Accumulating a body of such video data and sharing it with the learner and his/her coach will make both parties aware of the key biomechanics and how they are changing; they can then use this information to guide their learning/coaching. A number of studies have explored the process of motor skill acquisition and highlighted qualitative changes that arise in this process, including slumps (e.g., Suzuki & Ohnishi, 2007) [10] and changes in coordination/regulation of different body parts (freezing/freeing degrees of freedom; e.g., Bernstein, 1967[11]; Higuchi et al., 2002 [12]; Konczak et al., 2009[13]; Vereijken et al., 1992[14], 1997[15]). Using numeric values or graphs to visually model these qualitative changes (or indications that such changes will arise) will make the learner and his/her coach aware of the level of attainment of the target skill as well as the change thereof; they can then use this information to guide their learning/coaching. Thus, in addition to visually modelling the cognitive aspects of learning (as represented in learning discourses, for instance), visually modelling learners' motions and accumulating a body of such data may prove an effective strategy for supporting skill acquisition.

1.4 Ice Hockey as a Subject of Study

We chose ice hockey as the sport in which we would explore the potential for supporting skill acquisition by visually modelling cognitive and biomechanical aspects. The literature on ice hockey is limited when it comes to empirically verifying performance changes and coaching support; nonetheless, we regarded ice hockey as an appropriate subject to study in view of the findings of several studies on the sport. The literature has shown, for example, that cognitive skills, in addition to physical skills, are an important element among ice hockey players (e.g., Holt & Beilock, 2006 [17]; Thiffault, 1974 [18]). Thiffault (1974) [18]analyzed decision-making skills among ice hockey players of differing skill levels (elite and novice) by making them watch videos that simulated an ice hockey match situation. The study reported, among other things, that skill level influences decision speed. In a study by Hove et al. (2006)[19], participants used dynamic touch to infer the affordances of different hockey sticks. The study reported that ice hockey experience (novice vs. expert) affected how well they could perceive the affordances. Thus, the studies assert that physical and cognitive aspects are closely linked. In view of these findings, we assumed that ice hockey learners will, in the course of the learning process, experience changes in their motor and cognitive performances as well as changes in the relationship between motor and cognitive aspects. Ice hockey is appropriate for examining ways of visually modeling cognitive and athletic aspects and providing support accordingly. Therefore, we decided to focus on the skill acquisition process in ice hockey.

1.5 The Purpose

In this study, we sought to visually model the cognitive and biomechanical aspects of the process of acquiring ice hockey shooting skills. We did so with a view to deriving hints on how to support the process of shooting skill acquisition.

2 The Experiment

We conducted an experiment in which the participant performed a "slap shot," the most powerful shot in ice hockey. To perform a slap shot, the player winds up (raises the stick in the air behind the puck) and then aggressively swings the stick down so that the blade brushes the ice just behind the puck (see Figure 1). We focused on the slap shot because, of all the hockey shots, it requires the most extensive maneuvering, and it would therefore make for a relatively easy shot in which to visually model the player's changes in the skill acquisition process.

2.1 The Participant

The experiment was conducted on a single participant: a 21-year-old male with 8 years' experience in playing ice hockey. We selected this relatively experienced adult participant because the slap shot requires muscular strength. It is also too complicated a shot for novices to perform. The participant was a member of a university ice hockey club, so he may have had opportunities to practice the slap shot outside of this experiment (such as in team practice sessions). Nonetheless, we recruited this participant believing that being an active member of an ice hockey team, he would have all the more motivation to master the slap shot.

2.2 Experimental Setting

Rather than conducting the experiment on an actual ice hockey rink, we conducted it in an experimental setting—specifically, a hitting practice site with a

Fig. 1. Slap shot

plastic (rather than ice) surface. The participant did not wear skates during the experiment; his equipment was restricted to a hockey stick and a pair of gloves. To simulate an ice hockey goal, we used a “shooter tutor” (see Figure 2). The player took his shots from a distance of five meters from the goal. Figure 3 shows the experimental setting.

Fig. 2. Shooter tutors

2.3 Experimental Design

The experiment consisted of nine sessions over a roughly two-month period. Each session consisted of a pre-training test, training, post-training test, and report.

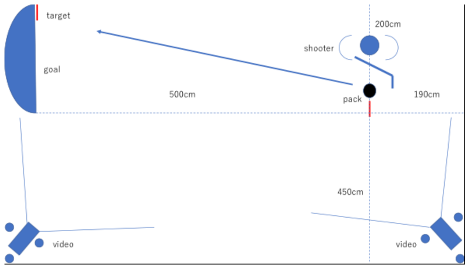

Fig. 3. Experimental setting

For each test, the participant had to attempt 15 slap shots. The training segment lasted for 10 minutes.

After the first and ninth sessions' post-training tests, we obtained motion capture data at three time-points (pre-hit, hit, and post-hit). Figure 4 describes the flow of each experimental session.

Fig. 4. Experiment

2.4 Instructions

For each test, the participant was instructed to slap shoot the puck as powerfully as possible into the upper right corner of the goal. For each training segment, he was instructed to practice this task for 10 minutes.

For the report segment, the participant had to respond to the following questions: "During today's training, what aspect(s) did you focus on in an attempt to master powerful and accurate slap shots? Please be as detailed as possible." "Why did you focus on this/these aspect(s)?" "For the next training session, what aspect(s) do you intend to focus on?" and "Why do you intend to focus on this/these aspect(s)?" The participant inputted his responses using a PC.

3 Analysis

3.1 Performance

To measure the speed of the participant's shots, we used FWD Powershot, a sensor that slides into the hollow shaft of a hockey stick. To measure shot accuracy, we counted the number of shots on target (shots that went into the upper right corner of the goal). We used the participant's post-training test performance as a measure of his advancement. Regarding performance feedback, the participant would have been aware of his shot accuracy (he could count the number of shots on target himself), but he was not informed about his shot speed.

3.2 Motion Analysis

After the first and final post-training tests, we recorded five motion capture data sets tracking the participant's knees and toes during his five shot maneuvers. We used two OptiTrack motion capture systems (OptiTrack V120: Trio; NaturalPoint) sampling rate=120 Hz. To record the data, we operated the systems synchronously with two video cameras (Handycam HDR-PJ390; Sony) running at 30 FPS.

When analyzing the video data, we identified three maneuver points in each video: swing-initiation, hit, and shot-end. "Swing-initiation" refers to the point when the participant commenced the downward swing. "Hit" refers to the moment the hockey stick hit the puck. "Shot-end" refers to the point when the participant commenced the downward swing after hitting the puck. We also identified pre-hit and post-hit maneuver phases. We defined the pre-hit phase as time from swing-initiation to hit, and the post-hit phase as time from hit to shot-end. We defined the overall shot maneuver time as the time from start to end. For each shot maneuver, we noted the total shot maneuver time as well as the time for each maneuver phase. We then compared the average times for the five shot maneuvers in the first session with those for the five shot maneuvers in the last session.

To eliminate noise from the motion capture data, we used data processing software (Motive 2.0.1, NaturalPoint; cutoff point: 10 Hz). Once we had eliminated the noise, we analyzed the height of the participant's knees and toes at each of the three maneuver points. We then compared the average positions for the five shot maneuvers in the first session with those for the five shot maneuvers in the last session. We did the same for the inter-knee and inter-foot distances.

3.3 Visualization of Action

Although analysis based on motion capture data is highly accurate, the issue is that experiments and analysis are time consuming. In this study, we aimed to establish a visualization system for practical applications and we considered visualization based on motion analysis with a monocular camera.

Cao et al. (2016) [16]released a library called OpenPose, which uses deep learning to estimate the 2D pose of individuals appearing in monocular camera images. Japanese company DeNA took OpenPose's algorithm and applied it to a deep learning framework called Chainer to create the application "Chainer-Realtime Multi-Person Pose Estimation." We used this application in our study after refining it. The application can detect 18 key points of the human body. We refined the application so that it could generate a CSV file with XY coordinates for the key points it detected. We then created a program that selects three of the detected key points and estimates a pose angle.

To consider visualization in this study, we conducted the following analysis using motion images taken using the camera at the back of the laboratory. We used motion images for one slap shot in the first and the last sessions, and the data for two seconds, or 60 frames, before and after the impact were subject to analysis. The angles between the shoulders, elbows, knees, and feet were subject to visualization. As skeletons are sometimes accidentally detected in the analysis, we calculated the moving average of nine sections.

3.4 Report Analysis

To analyze the participant' s reports, we used KBDeX (the application for visually modeling learning discourses that we mentioned in 1.2). We separately analyzed the participant' s responses to the four question items and plotted a network of the collocations in each sentence. We then analyzed this network focusing on collocations between collocating words associated with slap shot mastery—specifically, words describing maneuvers and words describing body-part positions. For each experimental session, we plotted a network and calculated its degree centrality.

We used the sum of the network' s node values as a measure of its degree centrality. Nodes that are connected to many other nodes will have a higher value. For example, take the network shown in Figure 5. There are five nodes: A, B, C, D, and E. Node A has three edges (it is connected to three other nodes), Nodes E, D, and C each have two edges, and Node A has one edge. Accordingly, Node A, being connected to 3/4 of the other nodes, has a value of 0.75. Nodes C, D, and E have a value of 0.5 (each is connected to half of the other nodes), and Node B has a value of 0.25 (it is connected to 1/4 of the other nodes). The sum of these values is 2.5. Therefore, this network' s degree centrality is 2.5.

An increase in node edges would result in higher degree centrality if the number of nodes did not increase. A decrease in node edges would result in lower degree centrality even if the number of nodes did not decrease (such an event never occurs). If edges and nodes both increased, the degree centrality would rise commensurate with the increase in edges. If nodes increased but edges did not, the degree centrality would fall. Thus, the network' s degree centrality will increase if a newly occurring word connects with the network, and will decrease if the new word does not.

4 Results

4.1 Performance

Figure 6 shows the post-training test results for each experimental session. The left vertical axis indicates shot accuracy and the right vertical axis indicates shot speed estimates.

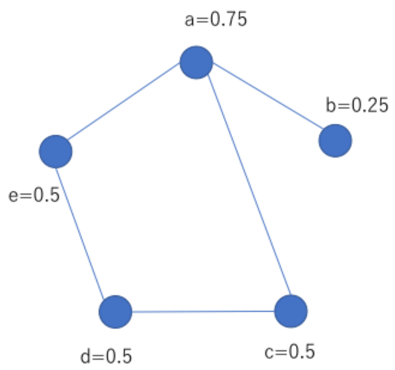

Fig. 5. Centrality

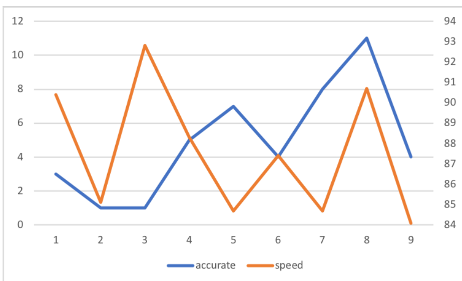

Fig. 6. Accurate and speed

We defined the first three sessions as "first sessions," the middle three as "second sessions," and the final three as "third sessions." Table 1 shows the average number of accurate shots and average shot speed for 1st, 2nd, and 3rd sessions. Figure 6 and Table 1 indicate that the participant' s shooting accuracy improved with successive experimental sessions. On the other hand, shot speed appears to have declined over the sessions. Looking at Figure 6, from the third to seventh sessions, accuracy and speed rise and fall contrastively (when one rises, the other falls, and vice-versa). Across the eighth and ninth sessions, they rise and fall together. This phenomenon suggests that the participant was at one stage sacrificing either accuracy or speed for the other, but that he subsequently acquired the form and cognition to achieve accuracy and speed at the same time. As we mentioned earlier, the participant could know his shot accuracy (by counting his successful shots), but he was unaware of his shot speed (we did not give him this information). Given this, we surmised that providing feedback on shot speed might be necessary to help learners master fast shots.

Table 1. Accurate and speed

	first	second	third
accurate	1.67	5.33	7.67
speed	89.4	86.8	86.5

4.2 Motion Results

Time Required for Shot Maneuver Figure 7 presents the average total maneuver time for the five shots executed in the first session (black bar) and that for the five shots executed in the last session (gray bar). The error bar indicates the standard deviation. In the first experimental session, the participant' s average maneuver time was 586.67 ms (SD = 38.01 ms). In the final session, it was 533.33 ms (SD = 23.57 ms). This result suggests that the participant reduced his maneuver time slightly as a consequence of training.

Figure 8 compares the average maneuver phase time (pre-hit and post-hit) for the five shots executed in the first session (black bar) with that for the five shots executed in the last session (gray bar). In the first experimental session, the participant took on average 333.33 ms (SD = 40.82 ms) for the pre-hit phase and 253.33 ms (SD = 29.81 ms) for the post-hit phase. In the final session, he took on average 253.33 ms (SD = 38.01 ms) for the pre-hit and 280.00 ms (SD = 18.26 ms) for the post-hit phase. These results indicate that, as a consequence of training, the participant' s pre-hit maneuver time reduced while his post-hit maneuver time increased.

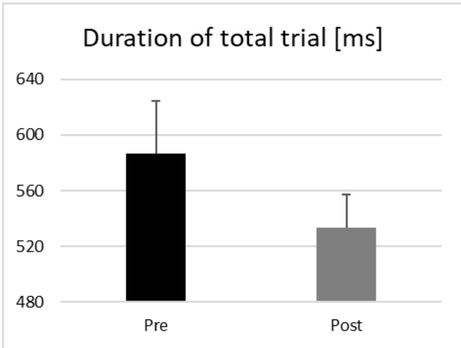

Fig. 7. Duration of total trial

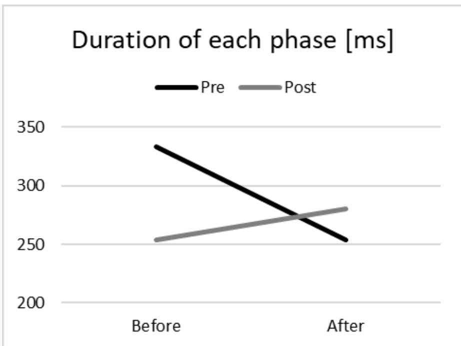

Fig. 8. Duration of each phase

Knee/Toe Spatial Data Figure 9 shows the average knee heights at the three maneuver points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation knee height was 53.12 cm (SD = 0.29 cm), the average hit knee height was 50.97 cm (SD = 5.34 cm), and the average shot-end knee height was 51.21 cm (SD = 4.59 cm). In the final session, the average swing-initiation knee height was 49.51 cm (SD = 0.74 cm), the average hit knee height was 49.27 cm (SD = 0.54 cm), and the average shot-end knee height was 50.67 cm (SD = 0.46 cm). These results indicate that, as a consequence of training, the participant lowered his left knee slightly during the pre-hit phase, thus lowering his center of gravity.

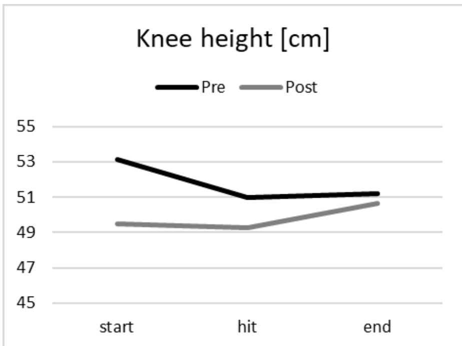

Fig. 9. Knee height

Figure 10 shows the toe heights at three points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation toe height was 5.52 cm (SD = 0.45 cm), the average hit toe height was 5.98 cm (SD = 0.96 cm), and the average shot-end toe height was 5.21 cm (SD = 0.47 cm). In the final session, the average swing-initiation toe height was 5.67 cm (SD = 0.27 cm), the average hit toe height was 5.48 cm (SD = 0.11 cm), and the average shot-end toe height was 5.39 cm (SD = 0.15 cm). These results indicate that the participant' s toe height changed little throughout the experimental sessions.

Figure 11 shows the inter-knee distances at three points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation inter-knee distance was 30.30 cm (SD = 5.12 cm), the average hit inter-knee distance was 30.00 cm (SD = 1.96 cm), and the average shot-end inter-knee distance was 35.45 cm (SD = 2.11 cm). In the final session, the average swing-initiation inter-knee distance was 36.99

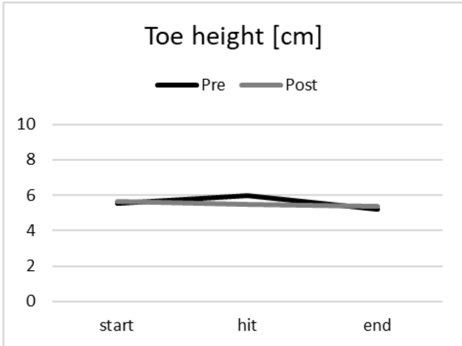

Fig. 10. Toe height

cm (SD = 2.07 cm), the average hit inter-knee distance was 38.05 cm (SD = 2.36 cm), and the average shot-end inter-knee distance was 41.18 cm (SD = 2.10 cm). These results indicate that, as a consequence of training, the participant' s inter-knee distance increased with successive sessions. The increased inter-knee distance meant that the participant could manipulate his body more fully during the shot.

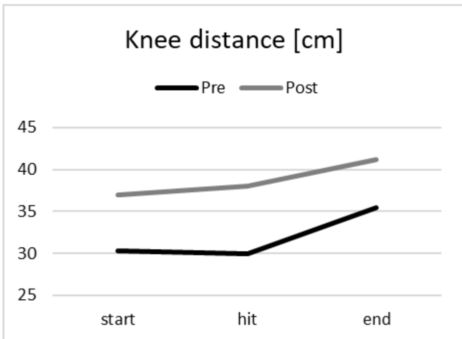

Fig. 11. Knee distance

Figure 12 shows the inter-foot distances at three points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation inter-knee distance was 48.92 cm (SD = 9.56 cm), the average hit inter-knee distance was 52.38 cm (SD = 15 cm), and the average shot-end inter-knee distance was 63.98 cm (SD = 11.1 cm). In the final session, the average swing-initiation inter-knee distance was 56.18

cm (SD = 2.87 cm), the average hit inter-knee distance was 57.10 cm (SD = 4.24 cm), and the average shot-end inter-knee distance was 61.21 cm (SD = 2.54 cm). These results indicate that, as a consequence of training, the participant' s inter-foot distance from swing-initiation to hit increased with successive sessions. The increased inter-foot distance meant that the participant could manipulate his body more fully during the shot.

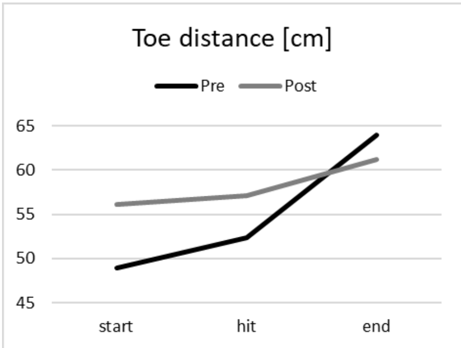

Fig. 12. Toe distance

4.3 Visualization of Action

Figure 13 shows the program utilizing the skeleton detection function of the monocular camera extracting the skeleton from the motion images.

Fig. 13. Uses deep learning to estimate

Figure 13 shows the skeleton being extracted from the images before and after the moment of the shot. Figure 14 shows the results of the analysis of the first and the last sessions of the experiment.

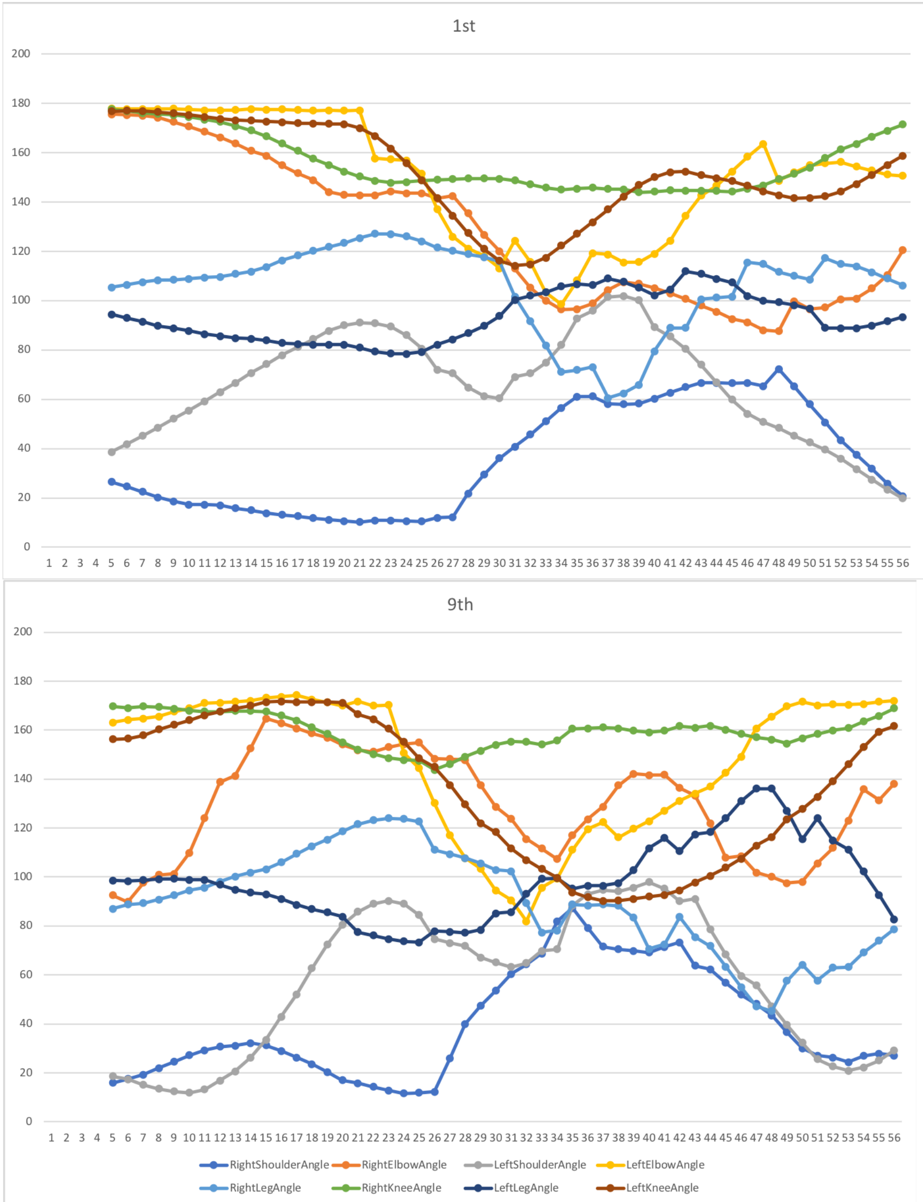

Fig. 14. Visualization of action

Figure 14 indicates that changes in the motion are seen, especially in the second half of the last session, compared with that of the first. The results are in agreement with the motion analysis based on motion capture data. The results of this study suggest that it is possible to extract skeletons and visualize motions by using images taken by a commonly available monocular camera.

4.4 Report Results

The following is an example of a phrase that the participant wrote in his report: "During the shots, I tried to avoid tensing up my body during wind-up." Such a phrase appeared at an average rate of 8.1 times per day. Focusing on such phrases, we analyzed 25 words related to slap shot mastery. Examples include "puck," "hands," "tried," and other words describing maneuvers or body parts.

Figure 15 shows the degree centrality across the nine experimental sessions. The horizontal axis indicates the number of sentences and the vertical axis indicates the degree centrality. The degree centrality fluctuated wildly in the early part of the experiment, but became more stable in the latter half.

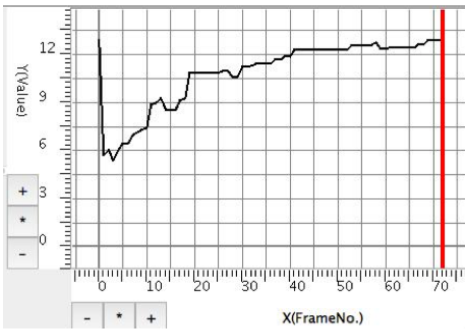

Fig. 15. Centrality

Figure 16 shows the networks of the nine experimental sessions. Numerous nodes appeared in the networks of the first 5 sessions, but the 6th, 7th, and 8th sessions' networks had fewer than 10 each. In the ninth session, the nodes recovered to a high level and presented a complex structure. Given the instability of the degree centrality during the first half of the experiment, the participant may have been figuring out slap shot strategies during this time. If the participant had figured the strategies out by the end of the fifth session, it would explain why we saw more stable networks for the sixth, seventh, and eighth sessions. The return to a complex network structure in the ninth session might reflect the fact that the participant performed less well in this session.

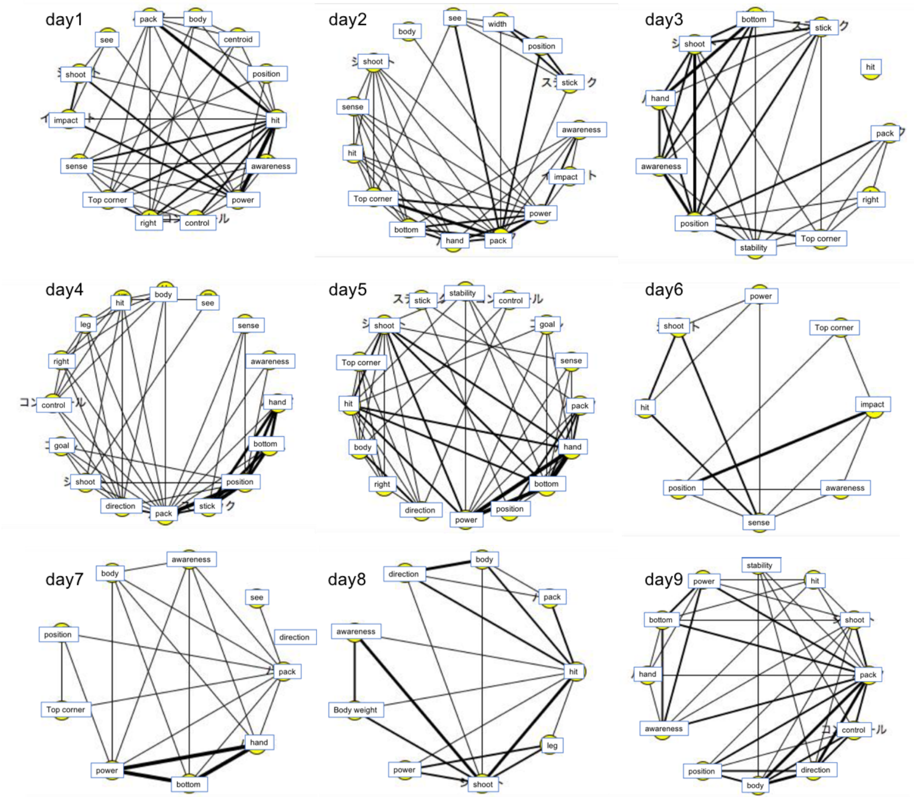

Fig. 16. Network

5 Summary

In this study, we sought to visually model the cognitive and biomechanical aspects of the process of acquiring ice hockey shooting skills. We did so with a view to derive hints for how to support the process of shooting skill acquisition.

Judging from the test results, the participant' s shooting accuracy improved over the course of the experiment. However, we did not observe any such improvement in his shooting speed.

The biomechanical analysis revealed that the following changes occurred over the course of the experiment: the participant' s overall shot maneuver time decreased slightly; his pre-hit maneuver time decreased while his post-hit maneuver time increased; his knee height, and thus his center of gravity, decreased; furthermore, his inter-knee and inter-foot distances widened. These results imply that the participant' s movements became more extensive, particularly during the post-hit phase.

We conclude that the approach we adopted in our study—conducting a network analysis (of the player' s reports) combined with a biomechanical analysis —is capable of visualizing the cognitive and biomechanical aspects of a player' s progress in respect to the performance indicators of shot speed and shot accuracy.

6 Future Outlook

Our findings have limited applicability because we conducted the study on only a single participant; moreover, we analyzed only a single ice hockey shot. Future studies should explore more cases. We did not inform the participant of the speed of his shots. However, to ensure that the research can be applied in coaching practice, it is necessary to obtain data on the learning effects of communicating such visualized information to the participant, and to ascertain how such data could help coaches support players. Finally, we conducted our experiment at an experimental site. Future studies should conduct experiments on a larger scale so that they are more applicable to ice hockey practice.

Acknowledgement

This work was supported by JSPS KAKENHI Grant Number JP16K16176.

References

1. Ministry of Education, Culture, Sports, Science and Technology, `http://www.mext.go.jp/component/a_menu/education/micro_detail/__icsFiles/afieldfile/2018/09/05/1384661_4_3_2.pdf`,
2. Storm, D., Kemeny, V., Leher, R., Forman, E., Visualizing the emergent structure of children' s mathematical argument, Cognitive Science, vol25,no.5, pp.733-773, (2001)

3. Zhang, J., Scardamalia, M., Reeve, R., Messina, R., Designs for collective cognitive responsibility in knowledge-building communities, The Journal of the Learning Sciences, vol.18, pp. 7-44, (2009)
4. Barabási, A.-L., Network theory: The emergence of the creative enterprise, Science, vol.308, pp.639 − 641, (2005)
5. Strogatz, S., Exploring complex network, Nature, vol.410, pp.268 − 276, (2001)
6. Nieminen, J., On the centrality in a directed graph, Social Science Research, vol.2, pp.371 − 378, (1973)
7. Matsuzawa, Y., Oshima, J., Oshima, R., Niihara, Y., Sakaia, S., KBDeX: A platform for exploring discourse in collaborative learning, Procedia - Social and Behavioral Sciences, Vol.26, pp.198-207, (2011)
8. J Oshima, R Oshima, Y Matsuzawa, Knowledge Building Discourse Explorer: a social network analysis application for knowledge building discourse, Educational technology research and development, vol.60, no.5, pp.903-921, (2012)
9. Nishiyama,T., Suwa,M., Visualization of posture changes for encouraging meta-cognitive exploration of sports skill, International Journal of Computer Science in Sport, vol.9, no.3, (2010)
10. Suzuki, H., Ohnishi, H., Non-random deviations from the power law of practice, Proceedings of the International Symposium on Skill Science 2007, pp.161-166, (2007)
11. Bernstein, N. A., The coordination and regulation of movements. Elmsford, NY: Pergamon Press, (1967)
12. Higuchi. T., Imanaka, K., Hatayama, T., Freezing degrees of freedom under stress: Kinematic evidence of constrained movement strategies, Human Movement Science, vol.21 pp.831-846, (2002)
13. Konczak. J., Velden. H. D., Jaeger, L.. Learning to play the violin: motor control by freezing, not freeing degrees of freedom, Journal of Motor Behavior, vol.41, pp.243-252, (2009)
14. Vereijken, B., Whiting, H. T. A., Van Emmerik, R. E. A., Newell, K. M., Free(z)ing degrees of freedom in skill acquisition, Journal of Motor Behavior, vol.24 pp.133-142, (1992)
15. Vereijken, B., Van Emmerik, R. E. A., Bongaardt, R., Beek, W. J., Newell, K. M., Changing coordinative structures in complex skill acquisition, Human Movement Science, vol.16 pp.823-844, (1997)
16. Zhe, C., Tomas, S., Shih-En, W., Yaser, S., Realtime multi-person 2D pose estimation using part affinity fields, Eprint ArXiv:1611.08050, (2016)
17. Holt, E. L. Beilock, L. S., Expertise and its embodiment: Examining the impact of sensorimotor skill expertise on the representation of action-related text, Psychonomic Bulletin & Review, vol.13, pp.694-701, (2006)
18. Thiffault, C., Tachistoscopic training and its effect upon visual perceptual speed of ice hockey players, Proceedings of the Canadian Association of Sport Sciences, Edomonton, Alberta, (1974)
19. Hove, P., Riley, A. M., Shockley, K., Perceiving affordances of hockey sticks by dynamic touch, Ecological Psychology, vol.18, pp.163-189, (2006)