






Development of a Simple Tracking System to Monitor Curling Stone Dynamics

Shimpei Aihara¹^a, Guanyu Chen²^b, Riku Hara³, Minori Nakagawa³, Ayumi Ogasawara⁴, Hitoshi Yanagi^{4,5}, Yoshinari Takegawa²^c, Takeshi Ito³^d and Fumito Masui^{1,6}^e

¹*Department of Sport Science and Research, Japan Institute of Sport Sciences, Tokyo, Japan*

²*School of Systems Information Science, Future University Hakodate, Hokkaido, Japan*

³*School of Information Science and Technology, The University of Electro-Communications, Tokyo, Japan*

⁴*High Performance Committee, Japan Curling Association, Tokyo, Japan*

⁵*Common Education Group, Kitami Institute of Technology, Hokkaido, Japan*

⁶*Information Communication Group, Kitami Institute of Technology, Hokkaido, Japan*


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Abstract: Curling, frequently called chess on ice, is a sport renowned for its strategic depth, making it essential to analyze stone dynamics for advanced tactical purposes. Systems have been developed to meticulously measure stone position and dynamics using camera imagery and devices affixed to the rocks. However, systems relying on multiple dedicated cameras and mounted devices encounter challenges related to portability and simplicity. Therefore, this paper presents the development of a simple tracking system employing a single camera to measure stone position and dynamics. The system uses deep learning for stone detection and tracking and calibration for coordinate calculation to visualize stone dynamics. This paper aims to support training and tactical planning using this tracking system. Experiments were conducted using the tracking system to assess its accuracy for static stones and the velocity of moving stones. The results indicated an average positional accuracy error of 0.02 m and an average velocity accuracy of 0.05 m/s, demonstrating the tracking system's high accuracy and practical feasibility.


1 INTRODUCTION


Curling is a sport where stones are thrown toward a target, called the house, on an icy surface, competing to score points. This sport was officially introduced as a medal event at the 1998 Nagano Winter Olympics. Since then, it has gained popularity worldwide. The Japanese women's curling team made history by winning Japan's first Olympic bronze medal in curling at the 2018 PyeongChang Winter Olympics. They followed it with a silver medal at the 2022 Beijing Winter Olympics, showcasing their talent on the global stage. As they aim for further glory, there are high expectations for improvements in their competitive abilities.


Curling, a sport renowned for its strategic and technical challenges, tests the precision and tactics of its players. The accuracy of each shot and the tactics employed can significantly impact the outcome of a match, directly affecting the team's victory or defeat. In matches at the level of the Japanese national team, a significant correlation was observed between the accuracy of shots and the points scored. Specifically, shot accuracy influences the point difference in matches (Masui, 2016), underscoring the importance of precision in shots to execute tactics tailored to the unfolding dynamics of the game. Thus, understanding the behavior of stones, which dictates the accuracy of shots, is paramount for executing precise shots.

^a <https://orcid.org/0000-0002-8513-0204>

^b <https://orcid.org/0009-0007-8754-6979>

^c <https://orcid.org/0000-0003-1947-0021>

^d <https://orcid.org/0009-0001-5253-1036>

^e <https://orcid.org/0000-0001-9979-8734>

Various systems using camera video files have been proposed to measure stone position and behavior. For instance, at the 2022 Beijing Winter Olympics and Paralympics, a system using video files from 42 dedicated cameras installed at the competition venue was introduced to measure stone position and trajectory (Shi, 2022). However, such systems requiring multiple cameras and dedicated installation at the competition venue pose challenges for simplicity and portability. Additionally, their use is limited to specific curling halls, further complicating their portability.

Methods have also been implemented by attaching devices called inertial measurement units (IMUs) to the handles of curling stones to measure their velocity, angular velocity, and displacement (Lozowski, 2016). However, attaching devices to curling stones might alter their original weight, potentially affecting their behavior. Moreover, such attachments are prohibited in official competitions, rendering them ineffective for measuring the behavior of stones used in tournaments.

Given the challenges of existing systems, an urgent need exists to introduce markerless, portable, and easy-to-use tracking systems in the competitive arena. Therefore, we propose a simple tracking system that uses highly portable cameras to provide feedback on the behavior of curling stones. This system aims to facilitate the easy measurement of stone behavior, contributing to training and tactical support.

This report discusses the accuracy evaluation of the proposed simple tracking system's analysis of stone velocity compared to laser velocity measurement equipment. The results will illuminate the proposed system's usefulness and accuracy, guiding further research and practical implementation efforts.

2 PROPOSED METHOD

The proposed simple tracking system relies on foundational technologies, including a detection model to identify stones within the image, a tracking model to follow the same stone across frames, and a calibration model to transform stone positions from the camera coordinate system to the global coordinate system. In this chapter, we discuss each technology constituting the proposed system.

2.1 Stone Detection Model

The stone detection model in this study was developed using the highly efficient You Only Look Once (YOLO) detector as the underlying model (Wang, 2023). YOLO is a popular object detection algorithm known for its real-time performance and exceptional accuracy in identifying objects within images. Transfer learning was employed with a custom dataset of curling stone images to fine-tune the YOLO detector for detecting curling stones. This approach leverages pretrained weights from a general object detection model and adapts them to the target domain, resulting in an optimized stone detection model for curling scenarios.

2.1.1 Dataset Creation

We recorded videos of competitions and practice sessions at various curling halls for dataset creation. An example of the filming setup is illustrated in Figure 1. We used commercially available video cameras, smartphones, and tablets to film from different vantage points near the ice sheet and spectator areas, varying the camera placement, angles, and shooting conditions, such as aperture, shutter velocity, sensitivity, and white balance, to ensure diversity in the acquired data. The video file encompassed various environments, including variations in the design and logos of the curling sheet houses, the colors and patterns of the background walls, and the lighting conditions. Additionally, since some curling rinks have glass windows separating the playing area from the spectator area, we included video files shot through glass.

Subsequently, we randomly extracted images from the captured video files and annotated the stones within the images. We surrounded the areas of the stones, excluding the handle parts, with bounding boxes and labeled them as red stone or yellow stone. Figure 2 shows an example of images from the dataset. We ensured coverage of various scenarios expected in curling scenes, including images where players overlapped with stones, brushes overlapped with stones, and stones overlapped with each other.

Staff trained in annotation tasks performed the dataset creation. Furthermore, multiple staff members mutually reviewed the annotated data, creating a high-quality dataset. This dataset, which is proprietary to us, is a collection of data and a crucial tool for developing a detection model.



Figure 1: Scene of the taking videos.



Figure 2: Sample images of the curling stone dataset.

2.1.2 Training the Detection Model

The YOLO v7 framework (Wang, 2023), known for its broad applicability and flexibility in object detection tasks, was the foundational model for our detection model. We initialized the model with parameter weights obtained from pretraining on the Microsoft Common Objects in Context (Lin, 2014), a comprehensive dataset of red-green-blue (RGB) images. Then, fine-tuning was conducted using our proprietary dataset comprising curling stone images.

We used the Adam optimization algorithm (Kingma, 2015) with a learning rate of 0.01 to optimize the model parameters. Thirty percent of the dataset was reserved for validation, and we selected the model parameters that yielded the lowest loss on the validation set. The training was performed on a PC (ELSA GALUDA G5-ND G450E) equipped with a Core i7-13700K CPU, GeForce RTX 4090 GPU, and 64 GB of memory. The programming language was Python, and the machine learning library was PyTorch.

The model was designed to take an RGB image as input and output the stone coordinates in the image and their respective colors (red and yellow).

2.2 Stone Tracking Model

The detection model identifying the stones in each image alone sometimes fails to detect stones due to occlusion caused by overlapping players or other stones and motion blur resulting from stone movement. Therefore, we implemented a model that tracks the same stones across video frames and fills in the missing frames by correlating consecutive detection results. In this study, we developed our model based on ByteTrack (Zhang, 2022), a method for tracking multiple objects. ByteTrack achieves stability, velocity, and accuracy through its Kalman filter-based algorithm. However, it must improve accuracy during complex movements and needs appearance information to prevent each stone switch identifier from switching. Therefore, we combined the motion and visual information of ByteTrack using attention mechanisms to achieve highly accurate tracking. This step enables the stable tracking of individual stones in the unique curling environment, where stones might become obscured by sweeping or where they might collide, resulting in complex stone movements.

2.3 Calibration Model

We developed a calibration model to transform the stone coordinates in the images to their global positions on the ice sheet. Obtaining coordinate values for calibration reference points in a real game or practice venue frequently requires more time. Also, calibration tools, such as poles or checkerboards, which are common in lab settings, could be more practical.

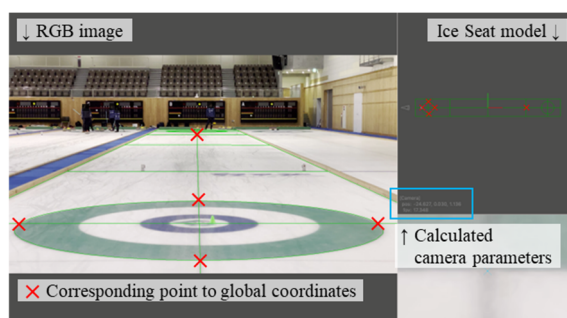


Figure 3: Screen capture of the calibration tool.

Therefore, we devised a method to calculate camera parameters from distinctive points visible in

the venue captured by the camera. In the game venues or arenas, lines are drawn on the court according to the rules regarding length and size, such as the circular mark called the house and the line known as the hog line in curling. Using known ice sheet information, we created a calibration tool (ice sheet model) to calculate camera parameters by providing the corresponding global coordinates for pixel coordinates (at least four points) in the RGB images. Figure 3 shows a screenshot of the developed calibration tool.

We used the Levenberg–Marquardt method (Moré, 1977) to calculate the camera’s position and orientation in three-dimensional space and the hill climbing method (Goldfeld, 1966) to determine the camera’s focal length, representing the internal camera parameters. With these camera parameters and the predefined three-dimensional shape information of the stone, we calculated the coordinates of the midpoint of the stone’s bottom surface on the ice sheet.

The calibration model does not require the entire curling sheet to be visible in the video file. Calibration can be performed as long as a portion of the curling sheet, such as a part of the house or the lines, is visible, offering the significant advantage of using video files filmed under any conditions. For example, even if the video file is a close-up of a specific area, analysis can be conducted if part of the curling sheet is visible. Therefore, video files captured from various camera positions, such as the audience seats or the coach’s area, can be accommodated. Furthermore, the calibration process allows accurate position data to be obtained, even if the filming angle varies, enabling the precise analysis of video files taken from oblique or irregular angles.

Our system is robust and reliable. It can analyze video files where only part of the house or lines are visible. This advantage makes it usable even if other objects are in the frame or part of the view is obstructed, ensuring that accurate data can be obtained in real-world match or practice environments where obstacles or other players’ movements might affect the video file.

This system’s flexibility is crucial for curling analysis. For example, it can consistently analyze video files from different venues, matches, or practice sessions with various camera settings and conditions, ensuring data consistency and reliability.

3 EVALUATIONS

We developed a tracking method for curling stones using the detection model described in Section 2.1, the tracking model described in Section 2.2, and the calibration model described in Section 2.3. Our method processes video footage a monocular camera captures to detect and track the curling stone, enabling us to calculate the stone’s position in sheet coordinates.

Three evaluations were conducted to validate the accuracy of the proposed method. These evaluations included the accuracy validation of the stone’s static position, the split time when the stone passed through specified intervals, and the stone’s velocity. Section 3.1 discusses the accuracy validation of the stone’s position, Section 3.2 covers the accuracy validation of the split time, and Section 3.3 explains the accuracy validation of the stone’s velocity.

3.1 Evaluation of Stone Positions

3.1.1 Data Acquisition Experiment

The experiment was conducted at the Argo Graphics Kitami Curling Hall. The proposed method was used to detect the positions of curling stones placed in known absolute coordinates with high accuracy. First, eight stones were placed on the ice sheet (Figure 4). The stones are labeled from A to H. The coordinate is centered at the middle of the ice sheet, with units in meters.

The recorded video file was analyzed using the proposed method to detect the stone positions. The positions detected were then compared to the actual positions of the static stones to evaluate the accuracy.

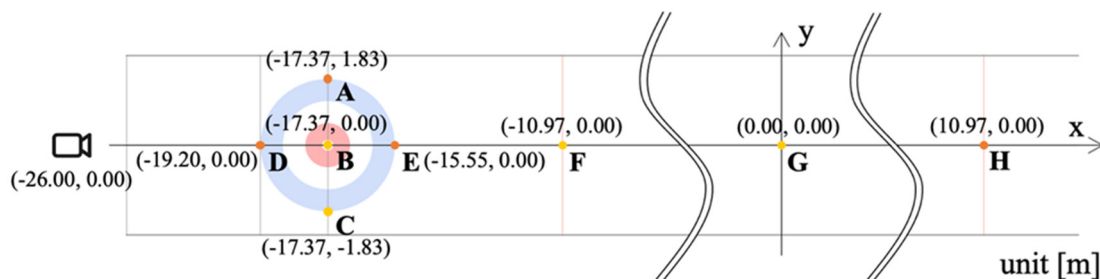


Figure 4: Position and coordinates of stones to be placed.

Figure 5 shows a frame from the recorded video file used for the evaluation. The accuracy evaluation involved calculating the differences between the static stone actual position data and the positions calculated using the proposed method. These positional discrepancies were statistically analyzed to determine the method’s accuracy.



Figure 5: Image of stones placed to evaluate positional accuracy.

3.1.2 Results

The accuracy evaluation results of the static positions of stones calculated using the proposed method are discussed. Table 1 shows the correct coordinates for eight stones, the coordinates calculated using the proposed method, and the error values. The “Correct Position” refers to the known 2D coordinates of points A–H on the curling sheet (Figure 4). The “Calculated Position” indicates the 2D coordinates determined using the proposed method. The “Error” represents the discrepancy between these two values. The L2 norm in the Error column indicates the Euclidean distance between the correct and calculated coordinates. Consequently, the average tracking system error for the eight stones was 0.02 m. The minimum error was 0.00 m for stone D, located approximately 7 m from the camera, and the maximum error was 0.03 m for stones G and H.

3.1.3 Discussions

The system used to measure the position and behavior of curling stones at the 2022 Beijing Olympics and Paralympics reported an accuracy of 0.30 ± 0.03 m over a measurement range exceeding 20 m (Shi, 2022). However, our proposed method achieves higher precision than previous technology, providing practical accuracy for real-world applications. Specifically, our method calculates the behavior of stones using video footage captured using a monocular camera, significantly improving the ease of installation and operation compared to a previous study (Shi, 2022), which required the permanent installation of multiple specialized cameras at the venue.

Furthermore, our proposed method can detect the position of a stone approximately 40 m away from the camera with an error margin of only 0.03 m. This high accuracy level is attributed to the high-quality dataset, as described in Section 2.2.1, where even the most petite stones in the images (those with few pixels) were annotated. This capability to detect stones across the entire sheet using only a single monocular camera has not been reported previously and is a highly innovative approach.

Traditionally, players and coaches recorded the stone positions manually using notebooks, which was time-consuming and limited in accuracy. Typically, positions were recorded with a granularity of approximately half to one stone’s width, leading to significant errors due to visual estimation. The proposed system can now record the stone positions simply by capturing video footage, resulting in simplicity and accuracy. This method provides much more precise data than manual recording, leading to significant advancements in analyzing curling strategies and techniques. Moreover, this method allows players and coaches to analyze practice and game performances more efficiently. The automated system reduces human errors and saves time and

Table 1: Errors between the correct values of the stone position and the calculated values of the stone tracking system.

	Correct Position [m]		Calculated Position [m]		Error [m]		
	x	y	x	y	x	y	L2 norm
Stone A	-17.37	1.83	-17.38	1.81	0.00	0.02	0.02
Stone B	-17.37	0.00	-17.38	-0.01	0.01	0.01	0.01
Stone C	-17.37	-1.83	-17.39	-1.82	0.01	-0.01	0.02
Stone D	-19.20	0.000	-19.20	0.00	0.00	0.00	0.00
Stone E	-15.55	0.000	-15.56	-0.01	0.02	0.01	0.02
Stone F	-10.97	0.000	-10.99	-0.02	0.02	0.02	0.02
Stone G	0.00	0.000	-0.02	-0.02	0.02	0.02	0.03
Stone H	10.97	0.000	11.00	-0.01	0.03	0.01	0.03
Average							0.02

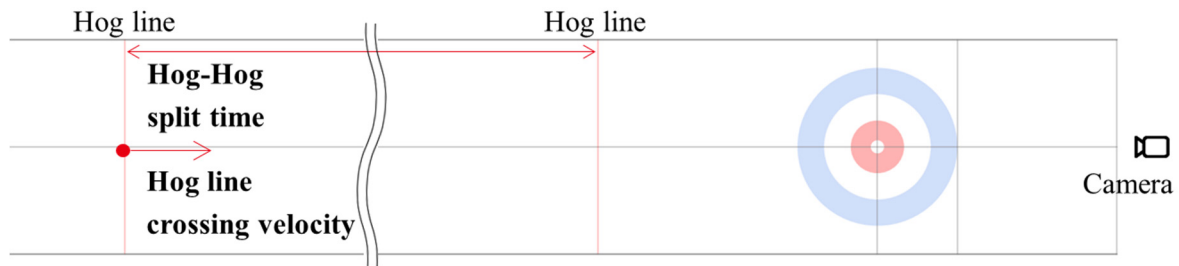


Figure 6: Image of evaluation indexes.

effort, enabling players to focus on improving their techniques, refining their strategies, and enhancing their overall performance.

3.2 Evaluation of Split Times

3.2.1 Data Acquisition Experiment

In curling, the hog–hog split time (H–H time) is typically used for evaluating stone velocity. As shown in Figure 6, the H–H time refers to the time a curling stone travels between the hog lines (a distance of 21.94 m) marked on the ice surface. Understanding the correct velocity is crucial for ensuring that the stone reaches its intended target accurately. During a match, the H–H time can be used to analyze players' performance in detail and make tactical adjustments. For example, players can adjust their throws based on different ice conditions and determine the optimal velocity for specific strategies.

In practice, accurately measuring the stone's velocity helps players improve the consistency of their throws, which is vital for skill development and increasing performance. Therefore, measuring the H–H time is crucial in curling. During training, the H–H time is measured using laser velocity measurement equipment (Rock Hawk – 2 beam), which is widely used in actual practice environments and has become a de facto standard used by most teams worldwide. The players and coaches use stopwatches to measure the H–H time during matches.

For the data acquisition experiment to evaluate velocity accuracy, we recorded videos of the stone being thrown and simultaneously measured the H–H time using the laser velocity measurement equipment. We then compared the H–H time calculated using the proposed method with the H–H time measured by the laser velocity measurement equipment. This comparison allowed us to assess the accuracy of the method.

During the experiment, shots with varying velocities were measured to ensure the collected data were balanced and bias-free. Specifically, stones were deliberately thrown at different velocities to

cover various velocities. Additionally, yellow and red stones were used to prevent color–based bias in the data. We collected data from 66 shots.

We used an iPhone 15 pro max to record the videos, positioning it approximately 1.4 m above the edge of the sheet (Figure 7 (left)). The resolution was set to 4 K, and the frame rate was 60 frames per second (fps). Figure 7 (right) shows the image from the recorded video. The laser velocity measurement equipment used was the same as in actual practice settings (Rock Hawk – 2 beam). Figure 7 (right) shows that the laser velocity measurement equipment was set up at the hog line, and the H–H time was displayed and recorded using an application developed by Tim Senger.

3.2.2 Results

In this evaluation, we compared the H–H time calculated using the proposed method (vertical axis) with that obtained using a laser velocimeter, considered the ground truth (horizontal axis) (Figure 8).

The results indicate a remarkably high correlation coefficient of 1.00 between the H–H times measured using the proposed method and the laser velocimeter. This result demonstrates that the proposed system achieves highly accurate H–H time measurements. Specifically, the mean absolute error between the H–H times calculated using the proposed method and the ground truth measured by the laser velocimeter was 0.10 seconds, with a standard deviation of 0.07 seconds.

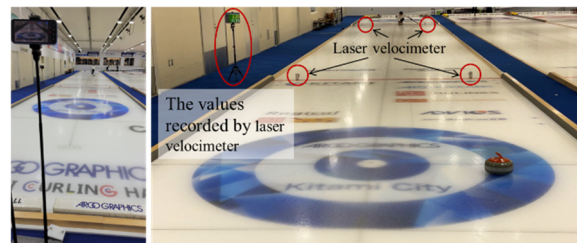


Figure 7: Camera setting (left). The sample image from the recorded video (right).

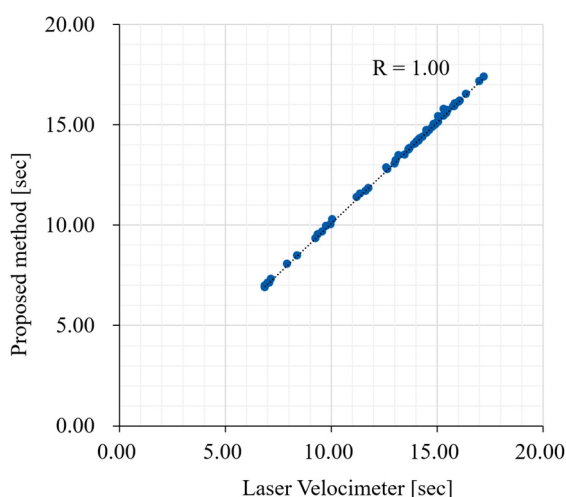


Figure 8: The H–H time correlation between the proposed method and the laser velocimeter.

3.2.3 Discussions

These results indicate that the H–H time measurement, which traditionally relied on expensive specialized equipment, such as laser velocimeters, can now be effectively achieved using only video recordings. While laser velocimeters offer precise velocity measurements, they are costly and require significant effort to set up. However, the proposed system uses video, making the measurement process more convenient and reducing economic burdens.

Furthermore, the proposed method is beneficial in actual competitive environments. Athletes and coaches frequently resort to manual timing with stopwatches, influenced by the measurer’s proficiency and fatigue and whether they use their dominant or nondominant hand. A study evaluating the errors in manual timing with stopwatches for 50-m sprints reported a systematic error of 0.27 s (Todou, 2018). Although the sports differ, this result indicates that our proposed model achieves higher precision than manual timing. The proposed method enables the swift and accurate measurement of the H–H time, which is crucial for evaluating player performance and conducting strategic analyses during competitions. This capability facilitates faster tactical decision-making and provides valuable feedback for enhancing player skills.

The proposed method has been confirmed as a viable alternative to traditional laser velocimeters, offering high-precision H–H time measurements. This advancement can significantly improve performance analysis methods in curling, leading to more efficient and effective training and strategy development.

3.3 Evaluation of Velocity

3.3.1 Data Acquisition Experiment

The velocity at which a stone crosses the hog line is typically used in curling. The hog line crossing velocity refers to the stone’s velocity as it passes over the hog line marked on the ice surface of the curling rink (Figure 7). Players must release the stone before it crosses the hog line, so this velocity is the approximate initial velocity of the stone in curling.

The initial stone velocity is crucial to ensure it reaches the target accurately. Throwing the stone at an appropriate velocity increases the likelihood of it reaching the desired destination. If the velocity is too high, the stone might overshoot the target, whereas the stone might not reach it if it is too low. Therefore, it is essential to measure and adjust the stone’s velocity accurately.

Accurately managing the throwing velocity enables players to achieve consistent throws. This consistency helps predict the stone’s trajectory and allows for strategic play. For example, the overall team tactics can be effectively executed by determining the optimal velocity for specific strategies. The hog line crossing velocity is measured using a laser velocimeter during training. This device, used in competitive environments, provides high-precision velocity measurements. The laser velocimeter is critical for supporting players’ skill development, as it allows for the precise measurement of their throwing velocities.

The data collection experiment for velocity evaluation was conducted as follows. First, videos of the thrown stones and the corresponding hog line crossing velocities were recorded using a laser velocimeter. Subsequently, the hog line crossing velocities calculated using the proposed method were compared with those measured by the laser velocimeter.

This experiment collected 66 shot data points. Figure 7 shows that the camera and laser velocimeter measurement conditions were consistent with those described in Section 3.2.1, ensuring uniformity in the data collection.

3.3.2 Results

The evaluation of the hog line crossing velocities yielded insightful results. A comparative analysis was conducted between the velocities calculated using the proposed method and those obtained through a laser velocimeter. Figure 9 illustrates this comparison through a correlation plot, where the vertical axis

denotes the hog line crossing velocities computed using the proposed method, and the horizontal axis represents the ground truth velocities measured by the laser velocimeter.

The evaluation revealed a high correlation coefficient of 0.98 between the velocities derived from the proposed method and those measured by the laser velocimeter, indicating exceptional accuracy in velocity measurement. Specifically, the absolute mean error between the hog line crossing velocities calculated using the proposed method and the ground truth velocities measured by the laser velocimeter was 0.05 m/s, with a standard deviation of 0.05 m/s.

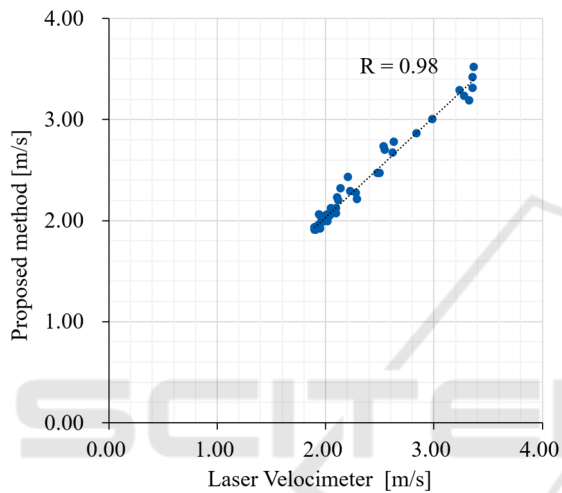


Figure 9: Correlation of the hog line crossing velocities between the proposed method and the laser velocimeter.

3.3.3 Discussions

These results demonstrate the practical effectiveness of the proposed method, particularly in accurately estimating the speed of stones more than 37 m away from the camera. Traditionally, measuring the speed of a stone crossing the hog line required expensive specialized equipment, such as laser velocimeters. However, this study shows that such measurements can be effectively performed using only video recordings, meaning a significant reduction in cost and setup complexity compared to traditional methods.

Furthermore, the accuracy of the proposed method improves as the distance between the camera and the stone decreases. The closer the camera is to the stone, the higher the resolution of the video, allowing for more detailed data collection. Figure 10 shows an example of a video image zoomed in on the delivery motion, which is the action of throwing the stone. Figure 11 shows the analysis results using the

proposed method. The correlation with the actual value measured by the laser velocimeter improved to 1.00. The mean absolute error improved to 0.02 m/s, and the standard deviation improved to 0.01 m/s. Thus, when conducting detailed delivery analysis, changing the shooting conditions to capture larger images of the stone can yield more accurate tracking data, allowing for objectively evaluating slight fluctuations and accelerations or decelerations during delivery.

Moreover, while traditional methods using laser velocimeters were limited to fixed-point speed measurements, the proposed method can continuously record the speed of the stone from the start of the shot until it stops, enabling a comprehensive analysis of the entire shot.

This advancement is highly significant for curling training and competition. Coaches and players can now analyze the movement of the stones in greater detail, enabling more precise technical guidance and strategic planning. By continuously recording the speed data of the stones, subtle adjustments can be made to the players' techniques and team strategies, improving overall performance.

Additionally, the proposed method allows for a detailed analysis of the relationship between the stone's speed and curl, which is critical for gaining new insights into curling strategy and technique. For example, it becomes possible to analyze how the stone's curl changes at different speeds and identify the optimal shots within specific speed ranges to achieve the desired curl.

Therefore, the proposed method opens a new dimension in data analysis for curling, providing coaches and players with a powerful tool for more efficient and effective training and strategy development. In addition, this method should improve individual player skills and enhance the strategic play of teams, raising the overall competitive level of curling.



Figure 10: Example of the zoomed-in video image of the delivery operation.

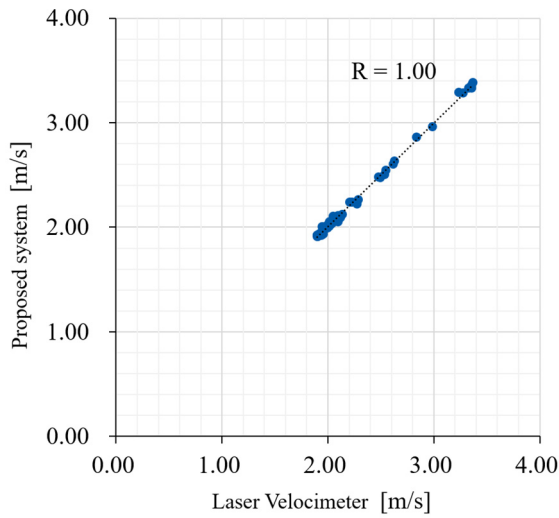


Figure 11: Correlation of the hog line crossing velocities between the proposed method and the laser velocimeter. The case of using a zooming video.

4 IMPLEMENTATIONS OF THE TRACKING SYSTEM

4.1 Overview of the Curling Stone Tracking System

We developed a tracking system for curling stones using the detection model described in Section 2.1, the tracking model described in Section 2.2, and the calibration model described in Section 2.3. Figure 12 shows the overview of the proposed system. This system uses the Swift programming language and operates on the Mac operating system (macOS). This system reads a video file captured by a monocular camera, tracks curling stones within the video, and visualizes the tracking results, allowing users to efficiently operate the system on a single computer and analyze the movements of curling stones.

Here is an explanation of the usage flow of this tracking system. First, the users load the video file they wish to analyze into the system. Next, the calibration model calculates the camera parameters from the video image. This calibration converts the coordinates in the video image to actual coordinates on the ice sheet. Then, using the stone detection and stone tracking models, the system detects and tracks the curling stones in the video, allowing the system to obtain time-series data on the positions of the curling stones on the ice sheet. Also, the time-series position data, velocity data, stopping position data, and other relevant information for each stone can be output as

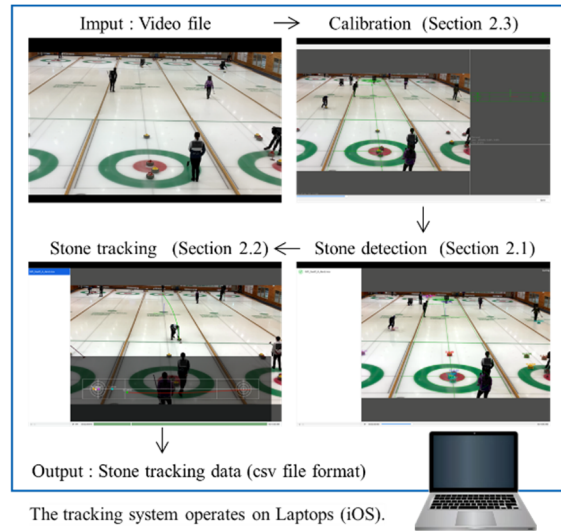


Figure 12: Overview of the tracking system.

Comma Separated Values (CSV) files for data storage and later analysis.

The processing velocity of the system achieves over 30 fps for 4 K video files, which was realized on a MacBook Pro (specifications: 10-core CPU, 16-core GPU, 32 GB memory). This high-velocity processing enables faster tracking of stone movements.

The system can analyze .mp4 and .mov format files captured by smartphones, tablets, video cameras, and other devices, allowing users to use video files captured on various devices. The system supports various filming conditions, such as the shooting position (e.g., spectator seats, coach seats, beside the ice sheet), the orientation of the ice sheet (front, side, diagonal), and whether the video file is shot through glass, ensuring accurate analysis from different viewpoints and angles. Additionally, the system can simultaneously analyze multiple stones on the ice sheet, allowing the tracking and analysis of the movements of multiple stones during matches.

Moreover, the system can be used for matches and practice sessions to analyze curling scenes in any context. Although curling venues might have different designs for the house on the ice sheet and various sponsor logos, the system can analyze video files from any curling rink. This advantage ensures consistent analysis results in different facilities and conditions.

4.2 Visualization of Curling Stone Dynamics

We visualized the stone dynamics from the obtained time-series position data. Figure 13 shows an

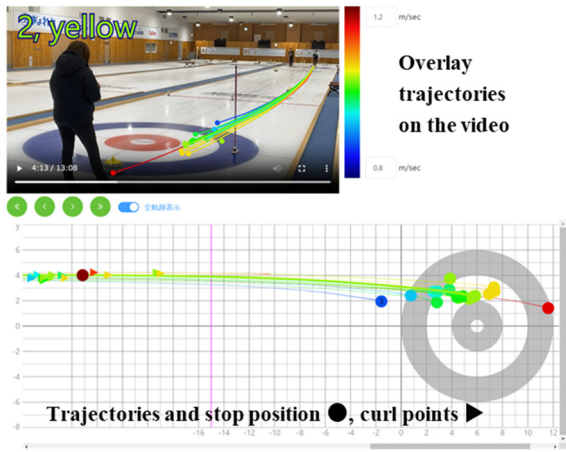


Figure 13: Examples of visualization.

example of stone dynamics visualization drawn using this tracking system. Additionally, it can draw overhead views of the stone movement trajectories. Figure 13 shows that the system can calculate and list each stone’s stopping position and the velocity at which it crosses specified lines.

Thus, this tracking system is a powerful tool for detailed analysis and the clear visualization of curling stone movements during matches and practice sessions. It is an innovative system that has not been reported before. This system let users quickly obtain data on stone movements, velocities, stopping positions, and more, aiding in game analysis and strategy planning. For example, by reviewing stone movements after a match, players can identify areas for improvement and measure the effectiveness of their practice. Additionally, the system can provide specific feedback to players during coaching.

Figure 14 shows that this system can analyze the trajectory and speed of curling stones and generate computer-generated renderings using only footage from a single camera. This capability opens possibilities for applications in television broadcasts and other media. Such graphics, unprecedented in traditional curling broadcasts, offer viewers a new way to enjoy the sport. For example, viewers can track the stone movements in real time, visually comprehend their trajectories and speeds, and better understand the strategies involved. Additionally, commentators can provide increased detailed and specific analyses based on this data, enhancing the viewing experience.

Moreover, this system achieves an analysis speed of over 30 fps for 4 K footage, operating on a MacBook Pro (specifications: 10-core CPU, 16-core GPU, 32 GB memory). The high processing speed makes it suitable for large-scale tournaments and

international matches, where real-time analysis is crucial, providing viewers with a seamless, lag-free experience. The ability to perform advanced analyses on standard hardware is a significant advantage.

This system is valuable for analyzing and visualizing curling stone movements. It has many applications, from match analysis and strategy planning to television broadcasts. Implementing this system promises to enrich the experience of playing and watching curling, making it more engaging and insightful.

Stone No	Color	H H time	Stop position		Hog line crossing velocity		Curl point		Curl width	Curl length
			x	y	far	near	x	y		
1	red	14.39	2.6	0.2	1.98	0.97	-41.3	3.5	3.3	43.9
2	red	13.88	4.8	1.9	1.99	1.07	-31.4	4.2	2.3	38
3	red	14.24	1.8	2.3	2	0.97	-29.9	4	1.7	31.7
4	red	14.08	4.2	2.3	1.98	1.04	-24.8	4.3	2	29
5	red	14.16	6.3	2.5	2.02	1.05	-26.2	4.3	1.8	32.5
6	red	14.58	5.3	2.7	2.03	1.01	-28.2	4.4	1.7	33.5
7	red	14.73	2.8	2.7	1.98	0.96	-29.6	4.5	1.8	32.4
8	red	14.17	4	2.9	2.04	1.04	-23.5	4.6	1.7	27.5
9	red	15.36	-4.2	2	2	0.82	-32.8	3.9	1.9	28.6
10	red	13.81	10.4	2.4	2.03	1.12	-21.7	4.2	1.8	32.1
11	red	13.39	12.7	2.7	2.1	1.24	-18.1	4.4	1.7	30.8
12	red	13.93	10	2.5	2.06	1.14	-22.8	4.3	1.8	32.8
13	red	15.28	-3.2	1.4	1.98	0.81	-36.8	3.7	2.3	33.6
14	red	14.58	1.5	2.3	1.98	0.96	-28.9	4	1.7	30.4

Figure 14: Values of stone dynamics analysis.

5 CONCLUSIONS

In this study, we developed a tracking system comprising a detection model to detect stones from images, a tracking model to track the same stone within a video, and a calibration model to convert stone positions from camera coordinates to global coordinates. We achieved a high level of accuracy, with an average position error of 0.02 m. Additionally, we demonstrated the practicality of the system by showing a strong correlation between metrics, such as the H–H time and hog-line crossing velocities, with those obtained from a laser velocimeter a de facto standard. Furthermore, we successfully visualized the dynamics of the stones from the position data.

The proposed system offers various beneficial aspects for curling:

- Training and skill improvement: Players can analyze stone behavior using the tracking system to enhance their skills, such as understanding stone speed and curl direction.
- Tactical and strategic improvement: Coaches and teams can use the tracking system to enhance their game strategies by analyzing stone movement and position data and studying opponents’ strategies and play styles.

- Match recording and analysis: The tracking system can record and analyze match data, enabling players and teams to identify tactical errors and areas for improvement for future matches.
- Player evaluation and selection: The system helps objectively evaluate players' abilities and performances, facilitating team selection and role assignment.
- Entertainment for viewers: The tracking system can provide entertaining content through television broadcasts or online streaming, enhancing viewers' understanding and enjoyment of the game.
- Fair judging in competitions: The tracking system accurately records stone movements, supporting fair judging by providing crucial information to referees and event organizers.
- Support for event management: The system can assist in event management by recording match progress and results, facilitating smoother event operations.

However, the tracking system also faces several challenges:

- Accuracy issues: Environmental factors, such as camera placement and lighting conditions, can affect the system's accuracy, primarily when relying on a single camera to detect stones.
- Real-time processing constraints: The proposed system's current workflow involves postcapture analysis on a laptop, limiting real-time data processing. Enhancing real-time analysis, such as on smartphones or tablets, would considerably benefit the system.
- Tracking and prediction capability: Currently, the system works by using computer vision to track stones, providing crucial position information. However, the potential for utilizing this data in more advanced analytical contexts, such as predictive modeling and tactical decision support, has yet to be fully explored. With the rapid development of machine learning technologies, such as Long Short-Term Memory (LSTM) networks, which excel in learning and predicting time series data, there is significant potential to design a system that leverages existing data to develop a tracking and prediction system. As illustrated in Figure 15, by utilizing the outcomes of this research along with terminal devices, we can not only visualize the current motion state of the stone in real-time, displaying information such as speed and angle,

but also predict the stone's future trajectory based on its initial motion state, using machine learning. This would provide athletes with more valuable information to enable more tactical interaction with the stone. The goal is to allow athletes not only to receive real-time feedback on the stone's movement but also to quickly understand potential motion trends and make informed actions based on experience and training, thereby improving performance. Moreover, the system's predictive capabilities could be extended to assist coaches in developing more precise training regimens by analyzing historical data and identifying patterns that correlate with successful outcomes, thereby facilitating continuous improvement beyond immediate match scenarios.

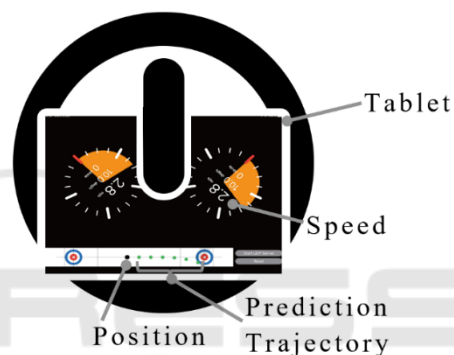


Figure 15: A tablet device on the stone visualizes the current stone dynamics and future trajectory.

- Enhancements to the user interface are necessary to make the system's operation and data analysis more user-friendly and accessible.

We aim to enhance the tracking system's performance and use and promote its adoption in curling competitions, training, and events by resolving these issues.

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