Visualization of Stone Trajectories in Live Curling Broadcasts using Online Machine Learning

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ABSTRACT

We developed a system for visualizing stone trajectories in curling games for live broadcasts. Robustly tracking a moving stone from curling video sequences is difficult because the stone is frequently hidden by the brushes held by the players and the players' bodies during their sweeping actions. Although a number of methods for visual object tracking have been proposed, real-time tracking under heavy occlusion is still a challenging task. We thus propose an online machine learning method for tracking a curling stone to deal with changes in its appearance. The method creates a candidate-object image, which eliminates background noises, and is used as input to the kernelized correlation filter (KCF) tracker. Coordinate transformation is also applied to the system to improve its operability. Experimental results showed that our stone tracker is more accurate and faster than other conventional tracking methods. The developed system was used at All Japan Curling Championships 2017 to display stone trajectories during live broadcasts.

CCS CONCEPTS

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KEYWORDS

visual object tracking; online machine learning; sports video analysis; curling game

1 INTRODUCTION

Visual object tracking is an important task in computer vision because the technology for it can be used in various scenarios, such as surveillance, robotics, and human-computer interaction [1, 2]. Sports video analysis is one scenario for which visual object tracking is strongly demanded [3-7], and it has been widely studied thanks to the improvement of computer vision technologies and the development of camera devices. Tracking results can be displayed as a trajectory in live sports broadcasts making it easier for TV viewers to see the movement of an object, as shown in Fig. 1.

Figure 1. Trajectories of curling stones broadcast at All Japan Curling Championships 2017.

Curling is a winter sport that is famous all over world [8]. Players throw heavy stones toward a target circle on an ice rink. The movement of the stone is strongly affected by the condition of the ice. For example, the stone may move slowly and be easily made to curve at a spot where many stones have already passed. The condition of the ice gradually changes as the game progresses. However, it is hard for TV viewers to understand ice conditions because they cannot see the traces of previous stones from normal camera images, as shown in Fig. 2. Therefore, we developed a novel system that visualizes stone trajectories in live curling broadcasts. The system can draw past trajectories on the ice rink, as shown in Fig. 1. The computer graphics (CGs) of trajectories help TV viewers to visually understand the condition of the ice rink.

To draw trajectory CGs, the positions of a stone at intervals during its movement have to be measured. However, measuring these positions from video sequences is very difficult because the stone is frequently hidden by the brushes held by the players and the players' bodies during their sweeping actions, as shown in Fig. 3. These occlusions cause frequent appearance changes, so it is hard for offline-trained classifiers [9, 10] to track a stone. Online learning trackers are thus suitable for the tracking of a curling stone. However, most online machine learning methods [11-15] require a heavy computational cost, making it hard to apply them to a live sports broadcasts. We thus used the kernelized correlation filter (KCF) [16-19], which is a tracker that is both fast and accurate, as the base of our tracking algorithm. We also improved the tracking accuracy of the KCF tracker by creating candidate-object images.

Changing the camera angle is another problem. Our system detects stones from a single camera image, so it measures stone positions using two-dimensional image coordinates. When the angle of a camera is changed, the positions of trajectories measured in the past are shifted from their correct positions. The system thus converts the stone positions to top-view coordinates by using perspective transformation. All trajectories can be displayed at the correct positions by way of top-view coordinates even if the camera angle changes.

We conducted several experiments to evaluate the performance of our developed system by using video sequences of actual curling games. The results showed that our developed system can robustly track a stone better than many conventional tracking algorithms. In addition, it could track a stone in real-time with a performance that satisfies the requirements for live broadcasts. The system was used at All Japan Curling Championships 2017, and the visualization of stone trajectories was appreciated by many TV viewers and commentators.

The contributions of this paper are as follows.

- A novel visualization system that displays stone trajectories in curling games was developed and used in live broadcasts.
- An online machine learning tracking method, which uses candidate-object images as input to the KCF tracker, is proposed to track objects under heavy occlusion.
- Trajectories, which are measured from different angles, can be drawn on the same camera image coordinates due to coordinate transformation.

The remainder of this paper is organized as follows. Related work is described in Section 2, the methods of tracking a stone and transferring its position are explained in Section 3, the results of the experiments are presented in Section 4, practical usage in broadcasting is introduced in Section 5, and the paper is concluded in Section 6.

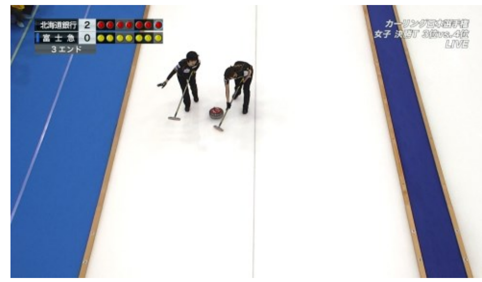

Figure 2. Normal broadcast image during shot in curling game. It is hard for TV viewers to understand ice rink conditions from such images.

Figure 3. Heavy occlusion during shot caused by players' sweeping actions. This makes stone tracking very difficult.

2 RELATED WORK

Visual object tracking is an important theme, so many algorithms for it have been proposed [1, 2]. It is also important for sports video analysis because the positions of players and a ball attract much interest from audiences [3-7].

Visual object tracking is basically performed by matching the representation of a target model built from the previous frame. One fundamental tracking technique is direct target matching by normalized cross-correlation (NCC), which uses the intensity values in the initial target region as a template [20]. The Lucas-Kanade Tracker (KLT) method is a feature point based tracker [21]. It detects feature points and calculates their optical flows to track a target region. The Median Flow tracker represents an object by using a bounding box and estimates its motion between consecutive frames by using the KLT method in the box [22]. Although these fundamental tracking algorithms are robust if target objects appear on a simple background without occlusions, it is hard for them to detect and track an object from a complicated background with occlusions.

Machine learning is also useful for object tracking as well as other computer vision tasks, such as image retrieval. The support vector machines (SVM) classifier is often used to improve tracking performance by recognizing target objects [9, 10]. Image features in target objects are learned by a supervised machine learning scheme beforehand, and the method robustly tracks objects by judging whether a detected object is a target or not with the classifier. However, it is hard for this pre-trained offline tracker to detect objects that change in appearance or objects under heavy occlusion.

Recently, online machine learning methods for object tracking based on discriminative classification have been proposed [11-15]. They build a model by distinguishing between the target foreground and the background on the basis of their appearance features. They build a classifier to distinguish target pixels from background pixels and update the classifier by extracting new samples in the next frame. The boosting method tracks objects by updating its classifier every frame, extracting positive samples from the target region and negative samples from outside it [13]. The Multiple Instance Learning (MIL) tracker is another online machine learning method [14]. It shows improved robustness to incorrectly labelled training samples. The Tracking Learning Detection (TLD) tracker simultaneously detects a target object in a video, learns its appearance, and tracks it [15]. It estimates its detector's errors and updates it to avoid these errors in the future. Although these online tracking methods are robust to appearance changes and occlusions, their calculations are slow because their computational cost is very high. Thus, it is hard to use them for live sports broadcasts.

Correlation filter based trackers have been regarded as state-of-the-art techniques for object tracking [16-19]. The kernelized correlation filter (KCF) is a novel tracking framework that utilizes the properties of the circulant matrix to enhance the processing speed [17]. Although the KCF is very fast and robust to changes in the appearance of a target, it still has difficulty tracking objects in cluttered scenes, such as scenes during sweeping actions in curling games.

We thus propose a robust method for tracking a stone from a curling video sequence for live curling broadcasts. Live broadcast programs require both accuracy and real-time computation. We thus used the KCF tracker as the base of our tracker, and the robustness of the tracker was improved by creating candidate-object images. Background noises are eliminated in images, and the size of the search area is optimized according to the size of the detected object. These improvements contribute to the robust tracking of curling stones, and trajectory CGs, which are drawn by using tracking results, are correctly displayed on the ice rink.

3 PROPOSED SYSTEM

3.1 Overview

Our developed system visualizes the trajectories of curling stones by tracking them from video sequences. Figure 4 shows a system diagram and actual pictures of the devices used in live broadcasting. Two fixed cameras images are input to the system because the direction from which a stone is thrown changes each end (round of the game) from one end of the playing surface to the other. We thus manually switched between the two cameras at each end in order to shoot the stone from a front angle. The same single camera image is input to subsequent devices, that is, the PC and inserter.

The PC detects and tracks the stone from the camera image and draws its trajectory CG on the basis of its detected positions. The CG is drawn just after the original shot finishes, and is composited on the camera image by the inserter. The PC plays key roles in this system, such as stone tracking, coordinate transformation, and trajectory CG drawing. We give details on these methods in the following sub-sections.

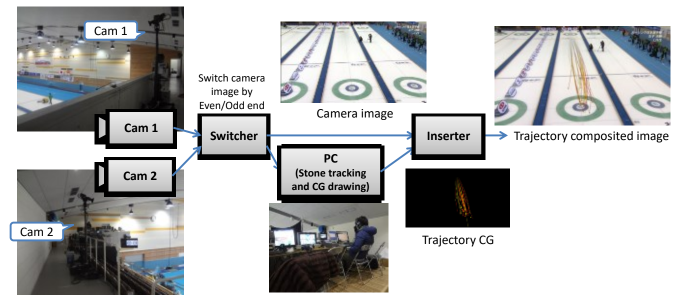

Figure 4. System diagram of our developed system.

3.2 Stone Tracking Method

3.2.1 Problems and proposed stone tracker

As mentioned, we used the KCF tracker, which is an online machine learning method, as a base tracker. It is robust to occlusion, and its processing speed is fast. Although it is more robust than offline machine learning methods against the appearance changes of a target, occlusion caused by sweeping actions is too much for steady tracking, as shown in Fig. 3 (in Section 1). In addition, the image size of a curling stone grows progressively larger in accordance with its movement. It thus is difficult for the normal KCF, which assumes a fixed search area size, to track a stone until it reaches its final position.

Our proposed stone tracking method thus creates a candidate-object image to eliminate background regions from original camera images and measure the size of the target object. This preprocessing improves the performance of the KCF tracker and enables a curling stone to be robustly tracked in the presence of heavy sweeping actions. A block diagram of the stone tracking method is shown in Fig. 5.

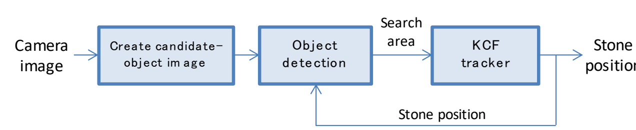

Figure 5. Block diagram of stone tracking method.

3.2.2 Candidate-object image

The system creates a candidate-object image from an original camera image as input to the KCF tracker. The object-candidate image is an image in which foreground objects, such as stones and players' bodies, are extracted from background regions, as shown in Fig. 6.

First, red and yellow regions, which are stone colors, are extracted from an original image by chromakeying in RGB color space. Some parts of the players' bodies might be extracted due to their uniform colors if they are similar to the colors of the stones. Next, morphological opening is applied to reject tiny bits of clutter. Then, small, large, and awkwardly shaped objects are eliminated from candidate objects by referring to their sizes and shapes. Only candidate objects are left in the image, and the image is input to the KCF tracking algorithm.

In addition, the proposed method detects a stone region in advance of the KCF tracker as shown in Fig. 5. An object that is the closest to the center of the search area in the candidate-object image is regarded as a stone object. The size of a search area is optimized on the basis of the size of the stone object. Our system can robustly track a curling stone even under heavy occlusion due to this candidate-object image and pre-detection of the stone object.

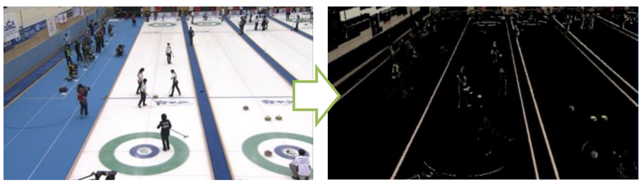

Figure 6. Original image (left) and candidate object image (right).

3.2.3 KCF tracker

The system tracks a stone from a candidate-object image by using the KCF tracking algorithm. In the KCF tracker, training samples are generated by considering all the circular shifts of search area $\mathbf{x}$ (this area includes a stone object and is larger than the object). M and N denote the width and height of x, respectively. For each sample $\mathbf{x}_{m,n}$, $(m, n) \in \{0, 1, \ldots, M\text{-}1\} \times \{0, 1, \ldots, N\text{-}1\}$, there is a Gaussian function label $y(m, n)$, which is computed by the following.

$$y_{m,n} = exp\left(-\frac{(m-M/2)^2+(n-N/2)^2}{2\sigma^2}\right) \tag{1}$$

The KCF tracker learns a classifier $\mathbf{w}$ with the following formula.

$$\min_{\mathbf{w}} \sum_{m=1,n=1}^{M,N} \left\|\mathbf{w} * \mathbf{x}_{m,n} - y_{m,n}\right\|^2 + \lambda\|\mathbf{w}\|^2 \tag{2}$$

, where λ is a regularization parameter. This calculation is performed by using fast Fourier transformation (FFT). In this paper, capital letters denote the discrete Fourier transform (DFT) of a vector. The classifier $\mathbf{w}$ is written in the frequency domain as:

$$\mathbf{W} = \frac{\mathbf{Y} \odot \mathbf{X}^*}{\mathbf{Y} \odot \mathbf{X}^* + \lambda} \tag{3}$$

, where $\mathbf{Y}$ indicates the discrete Fourier transform (DFT) of label $\mathbf{y} = \left\{y_{m,n} \mid (m,n) \in \{0,1,\ldots,M-1\} \times \{0,1,\ldots,N-1\}\right\}$. $\mathbf{X}$ denotes the DFT of search area $\mathbf{x}$, and $\mathbf{X}^*$ denotes the complex conjugate of $\mathbf{X}$. When an image patch (the patch includes the search area and is larger than the area) $\mathbf{z}$ is observed in the next frame, the correlation response map R is described as:

$$R = \mathcal{F}^{-1}(\mathbf{W} \odot \mathbf{Z}) \tag{4}$$

, where $\mathcal{F}^{-1}$ and $\mathbf{Z}$ denote the inverse FFT transform and the DFT of $\mathbf{z}$, respectively. Then, the KCF algorithm outputs the location of the stone by looking for the maximum point in response map R. The point becomes the center of the search area in the next frame.

The system accurately tracks a stone on the basis of the above online machine learning algorithm. Appearance changes caused by sweeping actions are trained frame by frame. A sample image captured during stone tracking is shown in Fig. 7. A trajectory is created by connecting the detected points of a stone, and trajectory CGs are drawn by calculating a spline curve that passes all detected positions. A sample of trajectory CGs was shown in Fig. 1 (in Section 1).

Figure 7. Processing image of stone tracking. Stone is being tracked even under heavy occlusion caused by sweeping actions.

3.3 Coordinate Transformation

3.3.1 Projective transformation

In curling games, the throwing direction of a stone is vertically switched in an ice rink between each end. Trajectories in even (odd) ends thus cannot be drawn in odd (even) ends because their directions are vertically opposite. In addition, trajectories in previous matches cannot be drawn when the camera angle is changed because these two camera coordinates are different. We thus used projective transformation to solve these problems.

Projective transformation is the projection from a planar surface to another one [23]. We can apply this transformation to curling game because stones move on a two-dimensional ice rink. We defined a top-view coordinate as a plane parallel with an ice rink, produced by dropping the height component of real 3D coordinates. Figure 8 shows the concept of projective transformation from a camera image to a virtual top-view image.

Projective transformation can be performed by using equations (5) and (6). The positions in the virtual plane (x', y') are calculated from positions on the camera image (x, y) and homography matrix $\boldsymbol{H}$. Elements h_1 to h_8 in the $\boldsymbol{H}$ are calculated by manual pointing of more than four corresponding points between the camera image and virtual plane beforehand. Every pixel in the camera image can be transformed to the virtual top-view image plane. All stone positions in a trajectory, which are on camera image coordinates, can thus be transformed to top-view coordinates by this operation.

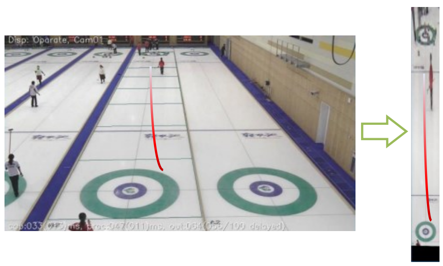

Figure 8. Concept of projective transformation. Camera image (left) is transformed to virtual top-view image.

$$x' = \frac{h_1 x + h_2 y + h_3}{h_7 x + h_8 y + 1} \tag{5}$$

$$y' = \frac{h_4 x + h_5 y + h_6}{h_7 x + h_8 y + 1} \tag{6}$$

$$\boldsymbol{H} = \begin{pmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & 1 \end{pmatrix} \tag{7}$$

3.3.2 Alignment of directions of stone trajectories

A trajectory on a top-view coordinate can be flipped by point symmetry because the coordinate is parallel with the ice rink. Each detected point on a trajectory can be vertically flipped. Figure 9 shows the concept of the alignment of the directions of a stone trajectory. After being flipped on the top-view virtual plane, a trajectory is re-projected onto the camera image by applying inverse projection.

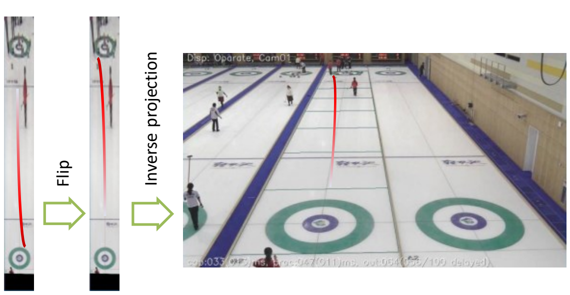

Figure 9. Alignment of directions of stone trajectory.

3.3.3 Coordinate transformation to different camera angle.

Projective transformation also enables the projection of a trajectory at a different camera angle. Figure 10 shows the concept of this operation. A trajectory on the top-view coordinate that was transformed from Camera A can be projected on the image of Camera B by applying inverse projection.

Using projective transformation, trajectories that have been measured from the opposite side or different angles can be projected on a current camera image. This improves the operability of our system, and stone trajectories can be drawn in a variety of scenes during games.

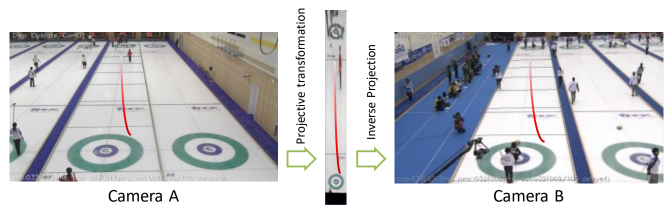

Figure 10. Displaying trajectory at different camera angle.

4 EXPERIMENT

4.1 Experimental condition

We conducted experiments to evaluate the performance of the proposed system. We set two cameras at a curling stadium, as shown in Fig. 4 (in subsection 3.1), and we recorded two official curling games played by top curling teams in Japan. These video sequences were used for training and evaluation data in these experiments.

Curling stones, which were thrown by the players, were manually plotted every 30 frame on a camera image coordinate, and they were used as the ground truth of stone position. These positions were also transformed to top-view coordinates to evaluate distance errors in meters.

4.2 Accuracy of offline machine learning tracker

Before the evaluation of our proposed online machine learning tracker, we evaluated the accuracy of a conventional pre-trained tracker [9] to confirm whether an offline machine learning is valid or not for tracking a curling stone.

One thousand and two hundred images patches were extracted from curling video sequences. Images that contained a stone were used as positive samples, and the other images were used as negative samples, as shown in Fig. 11. A half of the images were used for training, and the other half of them were used for evaluation. We trained a binary classifier, which used Gaussian kernel SVM [24], by using the training dataset. Table 1 shows the results of the binary classification with the classifier.

Although the tracking methods that are used in broadcast systems are required to have more than 90% accuracy, their F-measure value was only 72.0%. This fact indicates that it is hard for a pre-trained classifier to track a curling stone under heavy occlusion. Many stones in the positive image samples were partially hidden caused by players' sweeping actions. We confirmed that an online machine learning algorithm is needed for tracking a curling stone that frequently changes in appearance.

Figure 11. Positive and negative samples used in this evaluation.

Table 1. Accuracy of stone image identification with pre-trained SVM classifier

Precision	Recall	F-measure
84.7%	62.7%	72.0%

4.3 Comparison with other tracking methods

Next, we evaluated the performance of our proposed tracking method. We compared it with representative conventional tracking algorithms using the criteria of accuracy and processing speed. We used the SVM based offline tracker [9], which is the same algorithm as that in subsection 4.2, the optical flow based median flow tracker [22], and online machine learning trackers, that is, TLD[15], boosting[13], and MIL[14], as comparison methods.

Video sequences of 30 stone shots were used for this evaluation. The initial position of a search area, which was common for all trackers, was manually set, and each method individually tracked a stone until it stopped. We did not reset their search area even if they lost the stone. Error distances between manually annotated ground truth and estimated positions for each tracking method in the top-view coordinates were measured every 30 frame, and their average values were calculated. The average elapsed times for one tracking process for all tracking methods were also measured. The results are shown in Table 2.

The proposed method achieved the best accuracy among all the trackers. Its error distance of 0.34 was extraordinarily better than the other methods. This error is reasonable because the diameter of an actual curling stone is about 0.3 m. The error tended to decrease as the stone moved toward the camera because the size of the stone became larger. The error distance at the far side was indistinctive because trajectory CG around the stone shooting area were thinly drawn on long shots of the ice rink as shown in Fig. 1 (in Section 1).

Other online tracking methods tended to lose the stone during their tracking. They updated their classifier by training with a relatively few samples because of their high computational cost. In comparison, our KCF based tracking method updates its classifier with a large numbers of image samples in real time because the training is performed in Fourier space. The appropriate update of the classifier with many samples contributed to stable tracking under heavy occlusion. Figure 12 shows a sample of the tracking process in this evaluation. Although other trackers lost or mis-tracked the stone, our proposed tracker (red rectangle) could track a stone until reached its stop position.

The SVM based offline machine learning tracker achieved the best speed. However, the processing time of our proposed method was fast enough for real-time computation. A processing time of 5.9 msec is reasonable for keeping up with the 30 frames per second (within 33 msec) produced by broadcast cameras. In addition, accuracy should take priority over speed as long as the method is processed in real time. These evaluation results indicate that our proposed method is the best approach for tracking a curling stone, and it satisfies the requirements for use in live broadcasts.

Table 2. Comparison results with other trackers

	SVM[9] (offline)	Median Flow[22]	TLD[15]	Boosting[13]	MIL[14]	Proposed
Error [m]	9.52	26.1	11.9	9.82	3.23	0.34
Time [msec]	0.26	5.5	115.6	17.7	51.1	5.9

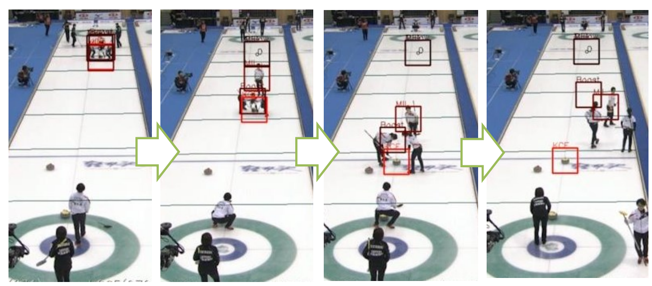

Figure 12. Sample of tracking process in this evaluation (red rectangle: our proposed tracker).

4.4 Effectiveness of candidate object image

Next, we evaluated the effectiveness of the candidate-object image by comparing the proposed method with the normal KCF tracker. Video sequences of 30 stone shots, which comprised the same dataset in subsection 4.3, were used for this evaluation. Average error distances were measured for the KCF and our proposed method.

The result is shown in Table 3. The error distance of our proposed method was much better than that of the normal KCF. This result indicates that the candidate-object image contributes to accurate tracking of a curling stone. The normal KCF tracker was improved by the object-candidate image.

Table 3. Average error distance of normal KCF tracker and proposed tracker

	KCF[17]	Proposed
Error Distance	2.00 m	0.34 m

5 PRACTICAL USAGE IN BROADCASTING

As can be seen, our developed system, which visualizes the trajectories of curling stones, was used for actual live curling broadcasts. The stone trajectories drawn by our system were broadcast in 12 games in a run of 7 days (from January 30th to February 5th) at All Japan Curling Championships 2017.

Two cameras were set at a curling stadium, as shown in Fig. 4 (in subsection 3.1), and their images were used for the input to the system. The system tracked a stone in real-time and drew trajectory CGs just after the original shot. Then, the accumulation of trajectory CGs was overlaid on the original camera images. The commentators explained the conditions of the ice rink and strategies of teams on the basis of the trajectory CGs, as shown in Fig. 13. TV viewers appreciated this visualization of the stone trajectories because they could visually understand the explanations of the commentator.

Trajectories drawn on an ice rink can be selected on the basis of their properties, such as the team, player, and shot type (take shot or draw shot). The pictures in Fig. 14 show variations in trajectory visualization. The properties were put on each trajectory when the trajectory was created. We plan to expand the variations of trajectory visualization by increasing the properties of a trajectory, such as successful/missed shot and fast/slow shot. In addition, we also plan to apply this system to other sports that are played on a flat surface, such as bowling and billiards, in the future.

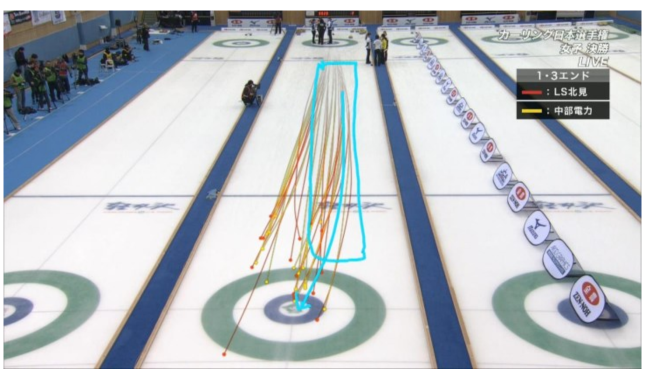

Figure 13. Broadcast image of stone trajectories (blue line: hand writing by commentator).

Figure 14. Variations in trajectory drawing (left: all shots thrown by red team, right: draw shots thrown by yellow team).

6 CONCLUSION

We developed a system for visualizing stone trajectories in curling games. Our system robustly tracks a curling stone in real time. We proposed an online machine learning method for tracking a stone that uses the kernelized correlation filter (KCF) as its base. We created a candidate-object image to improve KCF's tracking accuracy under heavy occlusion caused by players' sweeping actions. The system also enables a trajectory to be transferred to a different camera angle by using projective transformation. Experimental results showed that our stone tracker is accurate and fast enough for practical use in live broadcasts. The system was used during 12 live curling broadcasts of the All Japan Curling Championships 2017. The visualization of stone trajectories was appreciated by many TV viewers.

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