Visualization of putting trajectories in live golf broadcasting

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CCS CONCEPTS

• **Computer methodologies** → **Computer vision problems**;

KEYWORDS

Visual object tracking, machine learning, live golf broadcasting

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1 INTRODUCTION

We developed a system for visualizing golf putting trajectories that can be used in live broadcasting. The trajectory computer graphics (CGs) in a golf putting scene are useful for visualizing the results of past plays and the shape of the green. In addition, displaying past trajectories that were shot near the position of the next player helps TV viewers predict the ball movement of the next play. Visualizing the putting trajectories in this way offers TV viewers a new style of watching live golf tournaments and helps make the programs more understandable and exiting.

However, robust detection and tracking of a golf ball from video sequences is often quite difficult. For one thing, the ball is very small in comparison to the entire image of the putting green. Also, it is hard to differentiate the ball from other noise objects, such as players' caps and shoes. Finally, the ball is often hidden by players, and its appearance can be altered due to the players' shadows and changes to the weather.

To resolve these issues, we developed an online machine learning method for tracking the ball in golf putting. In our method, the classifier is updated every frame so that the ball can be robustly tracked even if its image features are changed.

The 3-D position of a ball is measured by calculating the intersection between the line-of-sight, which is from the sensor camera to the ball, and a 3-D model of the green undulation. Its trajectory CG is then composited onto broadcast camera images.

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This system was used in the Japan Open Golf Championship 2018 for displaying putting trajectories in a live broadcast, as shown in Figure 1. Commentators and TV viewers appreciated the visual effect because it brought them a new aspect and greater enjoyment in watching live golf.

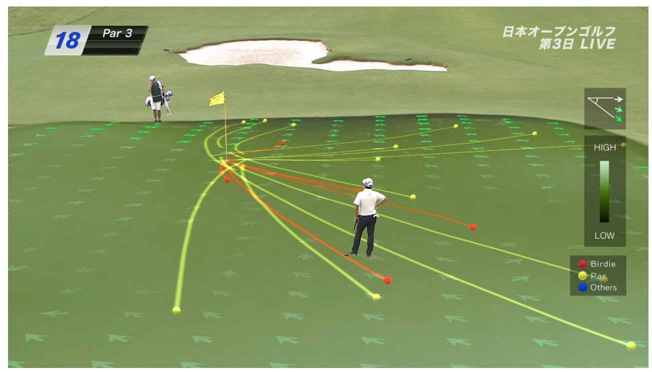

Figure 1: Broadcast images of putting trajectories in Japan Open Golf Championship 2018.

2 DEVELOPED SYSTEM

2.1 Overview

Figure 2 shows the overall data flow of our system. The ball position is measured from a sensor camera image by a ball tracking module and is translated into a 3-D position by a 3-D position calculation module. Then, the ball trajectory CG is drawn onto two different broadcast camera images by a 3-D CG drawing module.

Once the 3-D position of the ball is calculated, its trajectory CG can be drawn onto any broadcast camera images as long as their angle and field of view (FOV) data, which are related to pan, tilt, and zoom, can be acquired.

2.2 Ball tracking module

This module detects and tracks the ball from a fixed-sensor camera image that is set up nearby the green. The flow of the ball tracking module is shown in Figure 3.

First, it roughly extracts several ball candidate objects in the image on the basis of low level image features such as color, size, and shape. Then, a search region is manually set around a player. The ball is searched only in this region so as to avoid incorrect detection of other noise objects, such as players' caps and shoes.

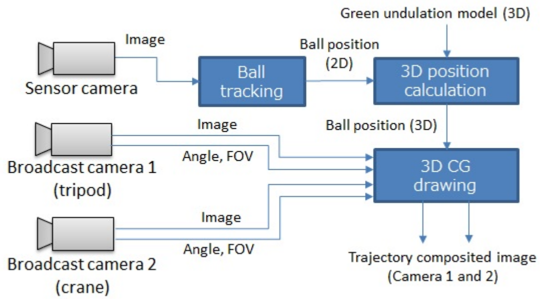

Figure 2: Overall data flow of our system.

Once a ball is detected in the region, it is automatically tracked until the ball stops or sinks into a cup.

We use an online machine learning method to track the ball because it often changes its appearance due to the shadows of the players or to weather changes. The Discriminative Correlation Filter with Channel and Spatial Reliability (CSR-DCF), a state-of-the-art method for visual object tracking, is the one we chose [Lukežič et al. 2018].

Calculations that are both fast and accurate are required for visualization systems that are used in live broadcasts. Although online tracking algorithms are generally slow, as they update the classifier every frame, our system achieves both accurate and realtime (30 fps) tracking by combining candidate object extraction with the CSR-DCF tracker.

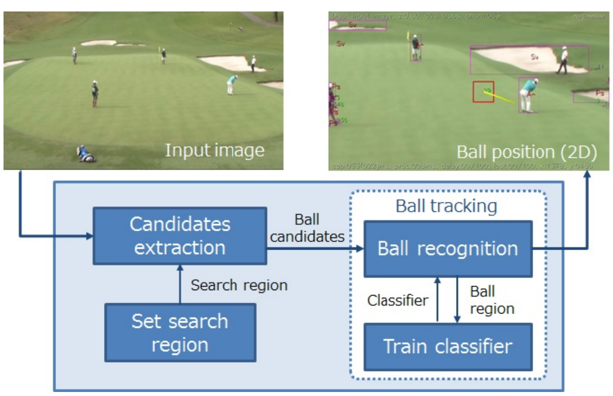

Figure 3: Process flow of ball tracking module.

2.3 3-D position calculation module

In this module, the 2-D ball positions in the image coordinates [pixel], which were measured by the ball tracking module discussed above, are translated into real 3-D positions [meter] in order to draw 3-D CGs and project them onto a broadcast camera image.

The 3-D position of the ball is measured by calculating the intersection of the line-of-sight, which is from the sensor camera to the ball, and the 3-D undulation model of the putting green. The undulation model was created by a 3-D range sensor prior to the game.

The system can be used in live broadcasting because all procedures are performed within the frame rate of a broadcasting camera (59.94 frames/second).

2.4 CG drawing module

The 3-D CGs of ball trajectories are drawn by connecting the 3-D positions of the ball, and then the trajectory CGs are smoothed by using Bézier curves. The colors of the trajectory CGs can be changed in accordance with their types, such as par and birdie.

The green undulation is visualized in addition to the ball trajectories through the use of arrows, as shown in Figure 1. Their directions and amount of gradients are calculated on the basis of the 3D undulation model. Although it is difficult to grasp the shape of the green from a regular camera image, TV viewers can easily understand it with the arrows.

3 EXPERIMENT

We evaluated the accuracy and speed of the ball tracking module through experiments. The average error distance [pixel] and average processing time within a single frame [msec/frame] were calculated over thirty video sequences of golf putting. Three conventional tracking methods –median flow [Kalal et al. 2010], tracking learning detection (TLD) [Kalal et al. 2012], and multiple instance learning (MIL) [Babenko et al. 2011] –were compared with the method we developed. The results are listed in Table 1.

Our method was the most accurate and was fast enough for use in live broadcasting (less than 33 msec/frame). The conventional tracking methods tended to make miss-detections of noise objects, while our module robustly tracked the ball by extracting ball candidates.

Table 1: Results of comparison with other tracking methods.

	Median Flow	TLD	MIL	Proposed
Error distance [pixel]	67.6	150.3	32.0	10.5
Processing time [msec/frame]	5	41	70	22

4 PRACTICAL USE

We used our developed system in the Japan Open Golf Championship held in October 2018. We set a sensor camera at the putting green of hole 18 and created all 120 putting trajectory CGs in a day. The trajectory CGs were projected onto broadcast images to visually display the results of past plays on the green, as shown in Figure 1. They were also used as a guide when a player shot a ball near the shoot position of the past trajectory.

We found that TV viewers could visually understand the results of past plays thanks to the trajectory CGs. They appreciated this video effect because it brought them a new way to watch golf programs, and it made the programs more understandable and exiting.

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