

# Curly: An AI-based Curling Robot Successfully Competing in the Olympic Discipline of Curling

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## Abstract

Most artificial intelligence (AI) based learning systems act in virtual or laboratory environments. Here we demonstrate an AI-based curling robot system named ‘Curly’ that competes on a real-world curling ice sheet. Curly encompasses (1) an AI-based curling strategy and simulation engine under consideration of the high ‘icy’ uncertainty, (2) the thrower robot enabled by autonomous driving with traction control, and (3) the skip robot that allows to recognize the curling field and stone configuration based on vision technology. The Curly performed well both: in classical game situations and when interacting with human opponents, namely, the top-ranked Korean amateur high school curling team.

## 1 Introduction

Numerous attempts have been made to apply AI technologies to real-world outside confined laboratory environments [Archibald *et al.*, 2009; Yee *et al.*, 2016; Ahmad *et al.*, 2016]. This is a hard problem since the real-world has numerous variables that vary over time, which can have a profound effect on the performance of AI. Moreover, the real-world has high uncertainties, which are too complex and too ill-defined to be modeled with the necessary accuracy. Thus it becomes necessary to encompass uncertainty into the modeling and furthermore to measure and approximate changes in real-world environments.

This work has chosen to use the complex game of curling as a test bed for demonstrating the interaction of an AI system and the real(slippery) world.

Curling (an Olympic discipline) is a turn-based game in which two teams play alternately on the ice sheet, requiring a high level of strategic thinking and performance. When we look at curling from an AI perspective, comparing with board games such as chess or go [Silver *et al.*, 2016; 2017], the following two parts are significantly different. Firstly, curling has a considerable



Figure 1: The AI curling robots play the curling game on a real curling ice sheet. (Left) The skip robot recognizes the game state using the location of stones. (Right) The thrower robot is throwing in order to deliver the stone to the target location chosen by the AI strategy engine. <https://youtu.be/yXygf8oz58k>

amount of legal moves because the game progresses in *continuous space* [Yee *et al.*, 2016; Ahmad *et al.*, 2016]. Secondly, because of stones’ collisions, curling requires a sophisticated and time-consuming physics-based simulation process to accurately describe and simulate possible legal moves for the next step [Ito and Kitasei, 2015; Ohto and Tanaka, 2017]. In recent years, studies on strategy-AI in curling area have been actively conducted in a virtual simulator environment [Yee *et al.*, 2016; Ahmad *et al.*, 2016]. In reality, however, ice has strongly varying conditions etc. so the uncertainties are higher than they may be expected from a simulation in the virtual world.

Note that the real curling game is played on the ice sheet covered with pebbles. The pebbles change their condition from time to time depending on the temperature, humidity, ice makers, elapsed time since the maintenance ended, amount of sweeping done during the game, etc [Denny, 2002; Nyberg *et al.*, 2013]. That is, when delivering curling stones using the same direction, force and curl, the trajectory of the stones will vary strongly over time. In addition, most of the strategic plays take place within the 1.83 meter radius of house region about 40 meters away. Compared with rather controlled (virtual) board games application (i.e., chess, go, etc.), the real-world application of curling AI is somewhat challenging.

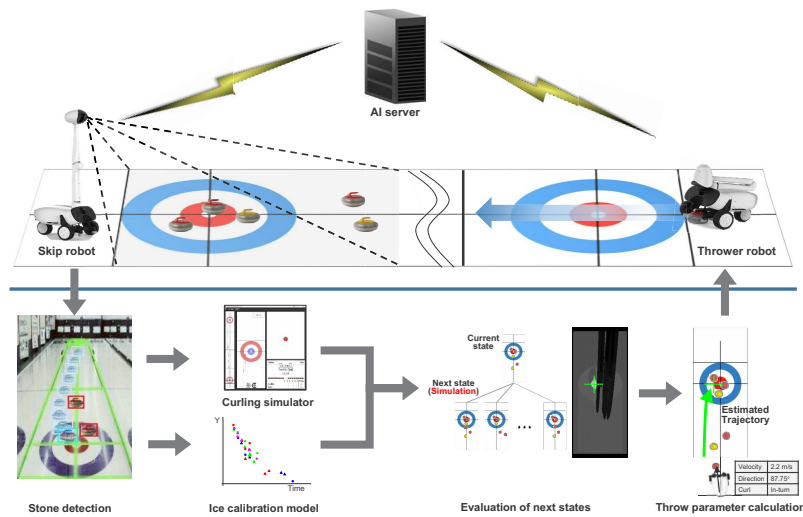


Figure 2: Proposed AI Curling Robot System: Curly. The system consists of thrower/skip robots, curling simulator, and strategy-AI. The system operation process consists of 3 steps as follows. 1) The skip robot recognizes the coordinates of the stones on the ice sheet and transmits them to the main server. 2) After receiving the coordinates, the main server establishes an AI-based strategy taking the uncertainty into account and sends it to the thrower robot. 3) The thrower robot delivers a stone with the strategy received from the server, and when all the stones stop, the opponent takes his turn again.

## 2 Methods

### 2.1 Curling Artificial Intelligence System

The main server part of AI curling robot system has the strategy-AI and curling simulator (Figure 2). Strategy-AI finds the optimal target position based on the stone’s coordinates, the estimated uncertainty and the current game status. We developed a physics-based curling simulator which is designed to adjust the parameters (i.e., throw angle, velocity, and curl direction, etc.). This simulator can help our AI to establish an optimal strategy in the real ice sheet environment. Intelligent compensation for uncertainty allows the robot to throw stones precisely into the desired target points on the real ice sheet environment (Figure 2) although all individual sub-components of our AI system are limited by errors of uncertainty.

#### Ice Calibration

The most striking difference between curling and other games is that it is almost impossible for a human or robot thrower to send the stone to the desired location (note that human players may in addition be hampered in their precision by being nervous). Calibration is to match the difference of the trajectory between the real ice sheet environment and the virtual physics simulator environment. It should be noted that the established strategies are quite different according to how precisely the inevitable uncertainty is approximated even in the same game situation.

#### Strategy-AI

We developed a strategy-AI based on reinforcement learning and tree search algorithm using physics-based simulations and evaluation values. To increase the success rate of the strategy regardless of uncertainty, we

consider the uncertainty area that represents possible reaching target points of thrown stone. In this manner, it becomes possible to perform not only stable but also competitive strategies.

### 2.2 Curling Robots

We constructed two identical robots (operated as skip and thrower modes respectively), each equipped with video analysis, data communication and throwing control modules including traction control. The thrower robot performs strategy on the ice sheet while holding and rotating a curling stone and releasing the stone by unfolding the gripper (Figure 1). The skip robot can recognize the coordinates of the stones or the trajectories of the moving stones (Figure 1).

## 3 Discussion and Conclusion

In the present study, an AI-based curling robot system that clearly shows the feasibility of applying AI technologies to highly uncertain real-world environments. Integrated planning, simulation, and uncertainty estimation were key to the successful and competitive throwing strategy in this icy environment.

Future studies will aim to use explainable AI techniques [Bach *et al.*, 2015] to gain a better understanding of critical shot impacts, thus allowing Curly and its makers to learn better from their mistakes.

## Acknowledgments

This work was supported by Institute for Information & Communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No. 2017-0-00521, 2017-0-01779).

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