Work-in-Progress: Hierarchical Control of a Catoptric Surface

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***Abstract*—The control of a catoptric (mirror-based) surface is decomposed hierarchically. The positioning control of individual mirrors is handled by low-level controllers for each drive motor, and the overall control decisions are guided by a Markov decision process.**

***Index Terms*—catoptric systems, hierarchical control, Markov decision process (MDP), daylighting systems**

I. Introduction

Daylighting, the use of natural light for illumination, is clearly beneficial in human-occupied spaces [1], [2]. Yet, daylighting design is dominated by passive window positioning and configuration [2] rather than active control mechanisms, except in a few cases [3].

To explore the possibilities of actively controlled daylighting systems, a catoptric (mirror-based) surface has recently been installed in the south facing glass façade of a campus building (see Figure 1) [4]. The catoptric surface is comprised of 650 mirrors, each with 2 independent degrees of freedom (pan and tilt), providing a full hemisphere range of motion.

With 256 possible positions per degree of freedom (180° range and 0.7° resolution), 2 degrees of freedom per mirror, and 650 mirrors, there are over 300,000 possible stable configurations of the catoptric surface. Add to this the desire to control mirror movement profiles (i.e., acceleration), and the number of configurations grows considerably.

In this paper, we describe our approach to controlling the catoptric surface as a device on the Internet of Things (IoT). The control is decomposed hierarchically, with low-level controllers (locally) handling individual mirror motions and high-level control (remotely) managing the desired position (and movement profiles) of the set of mirrors.

Fig. 1. Array of mirror units inside of the south-facing glass façade, Steinberg Hall, Washington University in St. Louis [4].

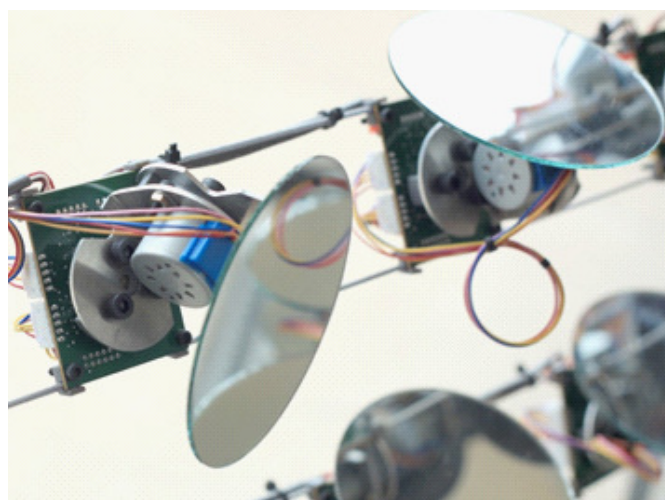

Fig. 2. Individual mirror units, each with pan and tilt control [4].

II. Individual Mirror Control

The pan and tilt of each mirror unit is driven by a pair of unipolar 12V stepper motors, commanded over an I2C bus by an Arduino Uno[1] on either end of each row of mirrors (see Figure 2) [4]. The two halves (east and west) have a Raspberry Pi[2] communicating with the Arduino Unos over USB, which also provides wireless connectivity to a remote PC running Rhino3D/Grasshopper.

The stepper motors are running open loop, (i.e., there are no shaft encoders in the system), so to establish known position each motor is driven to the physical stops (a reset position) and then the Arduino Unos accept motor movement commands that include mirror ID (x and y position in the surface), which motor (pan vs. tilt), direction, and number of steps. The local Arduino Unos make no attempt to retain position information, that is the responsibility of the higher-level system.

To enable movement profiles, we will extend the messaging

[1] https://www.arduino.cc
[2] https://www.raspberrypi.org

protocol and use the Arduino Unos to provide more nuanced timing in their motor movement commands. This is fairly straightforward in a stepper motor-driven system, in which individual step control is available.

The resulting catoptric surface is effectively an IoT device, which relies on network connectivity for high-level control.

III. Global Mirror Control

We are investigating the use of Markov Decision Processes (MDPs) to implement the high-level control of which mirror should be in what position. MDPs represent a general approach to modeling optimization problems and have been applied to a diverse set of application areas. Examples include: robotics [5], economics [6], experiment design [7], medical decisions [8], manufacturing [9], agriculture [10], real-time scheduling [11], and wireless spectrum management [12].

Here, we adopt the definition of Glaubius et al. [11] of a (discrete-time) MDP as a 5-tuple $(\mathcal{X}, \mathcal{A}, T, R, \gamma)$, with *states* $\chi \in \mathcal{X}$, *actions* $a \in \mathcal{A}$, and a transition system, T, which gives probability $P_T(\chi' \mid \chi, a)$ of transitioning from state χ to state χ' on action a. The reward function $R(\chi, a, \chi') \in \mathbb{R}_{\geq 0}$ describes the reward that accrues when transitioning from state χ to state χ' via action a, under a discount factor, γ, to ensure convergence of the long term reward.

For a catoptric surface with N_m motors, each of which has N_s steps, we define a state to be a vector of N_m motor positions, each of which has a value between 0 and N_s. This is illustrated for a single-mirror, 2-motor (pan and tilt) surface in Figure 3. The transitions represent single steps for the drive motors. Self-loops (not shown) would represent no motion. In the figure, only one motor at a time is allowed to be in motion. To support simultaneous motion, diagonal transitions would be added to the transition system, T. The figure generalizes to additional mirrors by adding two more dimensions per mirror.

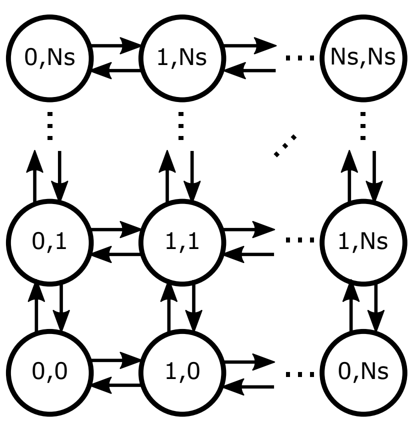

Fig. 3. Single-mirror, 2-motor MDP state space and associated transitions. Horizontal transitions represent moving the pan motor and vertical transitions represent moving the tilt motor.

We define the reward function, R, as having multiple components. First, it incorporates the match of the realized illumination pattern with a desired illumination pattern (using ray-tracing [4]). Second, it includes a measure of the impact of mirror motion on the reliability of the mirror assemblies. Third, it factors in the current positioning uncertainty due to running the motors open loop (i.e., low uncertainty at the range limit, growing uncertainty with each movement).

MDP theory assures us that there exists a policy (choice of action, a, in each state, χ) that maximizes the expected reward. While this policy is, in general, exponentially expensive to compute, we are exploring heuristics that closely match the optimal policy and are more computationally feasible in real time (so as to quickly accommodate changes in sun position, desired illumination pattern, etc.).

IV. Conclusions

The current state of the system is as follows: the physical installation is complete, the individual motor control software is complete and operational, and a number of variations on the global control MDP are being investigated. Extensions to the MDP that we are considering include: multiple motors in simultaneous motion, multi-step transitions that include acceleration profiles, and model reduction techniques to diminish the inevitable state-space explosion.

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