Projector-Camera Calibration on Dynamic, Deformable Surfaces

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ABSTRACT

Dynamic projection mapping (DPM) enables viewers to visualize information on dynamic, deformable objects. Such systems often comprise of a RGB-D camera and projector pair that must be calibrated apriori. Most calibration techniques require specific static calibration objects of known geometry. In this paper, we propose the first projector-camera calibration technique for DPM that uses the dynamic, deformable surface itself to calibrate the devices, without needing to bring in a static, rigid calibration object. Our method is hardware agnostic, fast, and accurate and allows quick recalibration.

Index Terms: Computing Methodologies—Artificial Intelligence—Computer Vision—Image and Video Acquisition

1 INTRODUCTION

Dynamic Projection Mapping (DPM) is challenging due to high-speed reconstruction of the moving surface and low-latency adaptive projection. Therefore, most prior works use custom hardware (e.g. high-speed, coaxial projector camera systems) [7, 12, 13] or markers for DPM [9, 10]. More recently, there have been systems that use a projector in conjunction with an RGB-D camera (e.g. Kinect) to achieve DPM without any custom hardware or printing [5, 6]. However, before the projector-camera system is deployed for DPM, it needs to be calibrated i.e. the intrinsic and extrinsic parameters of the devices need to be estimated accurately. This calibration is usually done using a static rigid object. Therefore, anytime the system is moved, this static rigid object has to be brought back in for recalibration.

In this paper, we propose the first work that achieves this projector-camera calibration using the dynamic deformable surface itself. We project a set of ArUco markers on the moving surface which is captured by the RGB-D camera. This is followed by a standard reprojection optimization that starts with the initial estimate of the intrinsics of the projector and converges to accurate intrinsic and extrinsic for both the projector and camera over a number of frames. Our method does not require any specific calibration objects of known geometry, therefore, anytime the projector-camera pair is moved, it can recalibrated quickly using the same dynamic and deformable surface that is being used for projection. Our work provides a new tool to calibrate projector-RGB-D camera pairs using moving and deformable surfaces.

2 RELATED WORK

There has been enormous work done in the domain of projector-camera calibration. Most methods use structured light scanning of a known calibration object to establish pixel correspondences between the projector and camera followed by calibration [1, 8, 11]. While [1, 8] require a planar object with printed patterns, [11] use an arbitrary object with known shape for calibration.

Moreno et al. [8] require a planar surface printed with a checkerboard pattern for calibration. The checkerboard is used to calibrate
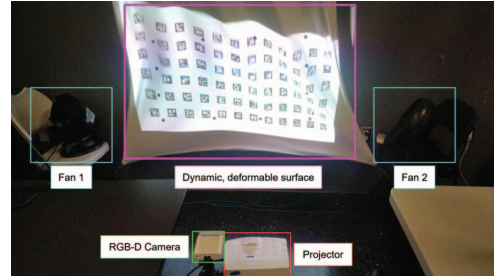
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Figure 1: Our setup, comprising a RGB-D camera and a projector positioned towards a dynamic, deformable surface.

the camera using Zhang's method [14]. The projector is treated like an inverse camera and is calibrated like a camera but using the projector-camera pixel correspondences generated from the structured light scan. Resch et.al [11] use structured light scanning and a precise 3D mesh of an arbitrary object (that can be obtained by a laser scan) to iteratively refine the calibration parameters of the projector-camera system.

3 METHOD

Our setup is a rig consisting of a projector and a RGB-D camera positioned to project on and capture a dynamic and deformable surface respectively. We assume that the RGB camera and depth camera are registered as is common in consumer RGB-D cameras. We start with a rough estimate of the projector focal length estimated using methods such as [2, 4, 8]. This can be done once for a projector of the same brand and make. If the camera API provides the intrinsics, we use those as an initial estimate, though we do not require it.

Projector and Camera Models: We model both the projector and camera with a pinhole camera model extended by a lens distortion model that include three radial and two tangential distortion coefficients. We assume that the RGB-D camera is at the origin, looking down the positive Z-axis. This makes the camera extrinsic matrix to be identity and we need to determine the camera intrinsic matrix and distortion coefficients only. However, we do need to determine both the intrinsic and extrinsic parameters of the projector with respect to the camera to calibrate the system.

Image Acquisition: In order to successfully calibrate a projector-camera unit, for the 3D surface coordinate d_i, we need the 2D camera pixel c_i that images it and the corresponding 2D projector pixel p_i that illuminates it. Since we address moving and deformable surfaces, we require a way to determine the camera-projector pixel correspondence using only one frame. Therefore, we choose to project a grid of ArUCo markers [3]. The location and the IDs of the ArUCo markers are estimated from the RGB-D camera captured images of the projected sequence. Using the IDs of the detected markers, we establish pixel correspondences between the RGB camera pixels and the projector pixels of that marker. Since the RGB camera and depth camera are registered, we can assign a 3D point to each pixel correspondence as well (see Figure-2).

Camera-Projector Calibration: Once we have correspondences between projector pixel, camera pixel and 3D point, we use a non-
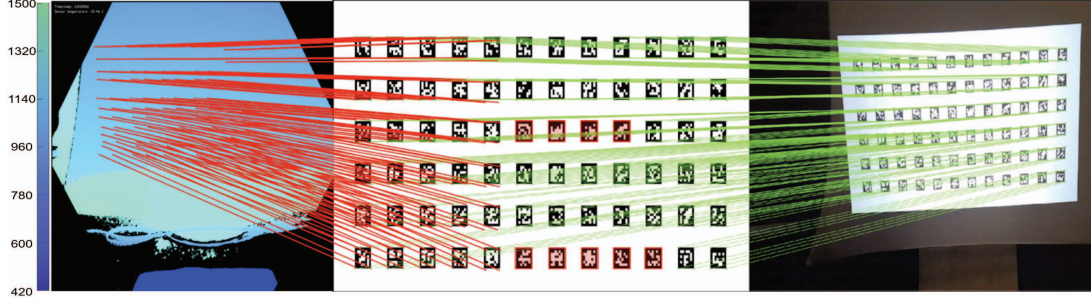
Figure 2: (*Left*) The depth map (in mm), (*Middle*) the projected image and (*Right*) the camera image. The corresponding pixels at the corners of the ArUCo markers between the projector, depth map and camera image are shown by the red and green lines respectively. Markers that were not detected in the camera image are highlighted in red.
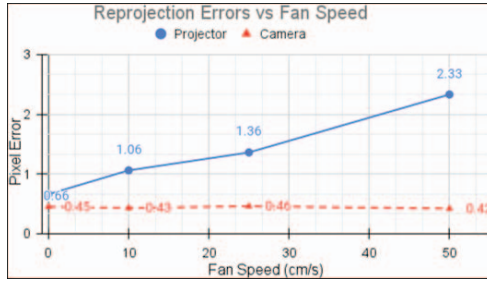

Figure 3: Projector-camera reprojection error against surface speed.

linear optimization that minimizes the reprojection error and compute the parameters for the camera and projector separately. We achieve this using the correspondence between the 2D pixel and 3D points. Let $\{p_i^t, c_i^t, d_i^t\}$ denote the i-th correspondence at time t. Let $\{K_c^t, D_c^t\}$ denote the camera intrinsic matrix and distortion coefficients at time t, and $\{K_p^t, D_p^t, R_p^t, T_p^t\}$ the projector intrinsic matrix, distortion coefficients, rotation and translation respectively, at time t. We optimize for the calibration parameters by minimizing the camera and projector reprojection errors E_c^t, E_p^t:

$$\arg\min_{K_c^t, D_c^t} E_c^t = \frac{1}{2}\sum_i (|c_i^t - \text{project}(d_i^t; K_c^t, D_c^t))^2 \quad (1)$$

$$\arg\min_{K_p^t, D_p^t, R_p^t, T_p^t} E_p^t = \frac{1}{2}\sum_i (|p_i^t - \text{project}(\tilde{d}_i^t; K_p^t, D_p^t, R_p^t, T_p^t)|)^2 \quad (2)$$

4 RESULTS

We implemented the proposed system with an Azure Kinect RGB-D camera and an Optoma EH200ST (short throw) projector on a dynamic, deformable surface. We placed two fans on either side of the surface to generate random waves and ripples across the surface and tested our calibration for various speeds of the fans (see Figure-1). This helped us to study the impact of the movement of the surface on the accuracy of our calibration technique. To estimate the surface velocity quantatively, we took the average of difference between same pixels of two successive depth maps. We quantified calibration accuracy using reprojection error onto camera and projector images (Figure 3). The camera reprojection error of less than 0.5 pixel does not get impacted by the movement of the surface. Even at the highest speed, our projector reprojection error is less than 4 pixels – less than 0.4% when considering the size of the projection image.

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