Realistic Simulation Environments to Achieve Visual Servoing on Soft Continuum Arms in Constrained Environments

Shivani Kamtikar*[1], Eric Ji[2], Naveen Kumar Uppalapati[3], Girish Krishnan[4], Girish Chowdhary[1]

1. *Department of Computer Science, University of Illinois at Urbana-Champaign, UIUC, USA*
2. *Department of Electrical and Computer Engineering, UIUC, USA*
3. *National Center for Supercomputing Applications, UIUC, USA*
4. *Industrial and Enterprise Systems Engineering, UIUC, USA*

Keywords: computer vision, agricultural robotics, sim2real, visual servoing, soft arms

Abstract:

Visual servoing is a popular control strategy for soft continuum arms (SCA) which involves manipulating the arm using visual inputs. Robust visual servoing involves various challenges, such as precise feature extraction and obtaining accurate control models and sensors that estimate the shape of the arm (Rus et al. 2015). These challenges are amplified in cluttered, semi-structured, and unstructured environments. Another major challenge comes from difficulties in recreating real-world workspaces for training, testing, and experimentation. Hence, there is a need to develop simulation environments that mimic real-world settings for testing methods before taking them to the field.

Our previous method of visual servoing on SCA used deep neural networks to estimate SCA's 3D position and orientation (Kamtikar et al. 2022). This method led to reliable reach-control of soft arms in structured, uncluttered environments. However, if we want to perform reach-control of soft arms in environments closer to agricultural field settings, we need to extend the workspace to include clutter.

Reaching a target while avoiding or leveraging obstacles produces challenges such as determining the position targets and planning a path to reach the target while avoiding the obstacles. Our path planning method uses 3D reconstruction of scenes to determine the position of targets in the workspace. Simulation environments are useful to train and test the method before taking the SCA to the actual field. These simulation environments act as “digital twins” and need to be as realistic as possible to get accurate and precise testing scenarios.

We propose implementing and using realistic simulation environments for robot learning tasks in agricultural settings. The rendered 2D RGB images obtained from the simulation environments are passed through a 3D reconstruction algorithm (Sarlin et al., 2019; Sarlin et al., 2020) to test their effectiveness in generating 3D point clouds. The obtained 3D point clouds are then utilized to determine the location of targets in the scene for path planning.

Blender is a popular 3D computer graphics software used in many computer vision tasks (Cartucho et al., 2021; Zdziebkoet al., 2021). We created multiple realistic simulation environments using Blender that can be used for various robot learning tasks such as manipulation and navigation. Each environment consists of several obstacles and targets created using geometrical meshes. Multiple cameras in the workspace provide different viewpoint renderings of the environment.

To create realistic environments, we considered multiple factors such as textures, lighting, shadows, the shape of the objects, etc. If the simulation environment is not realistic enough, the 3D reconstruction algorithm finds it challenging to identify key points owing to smooth textures, perfect

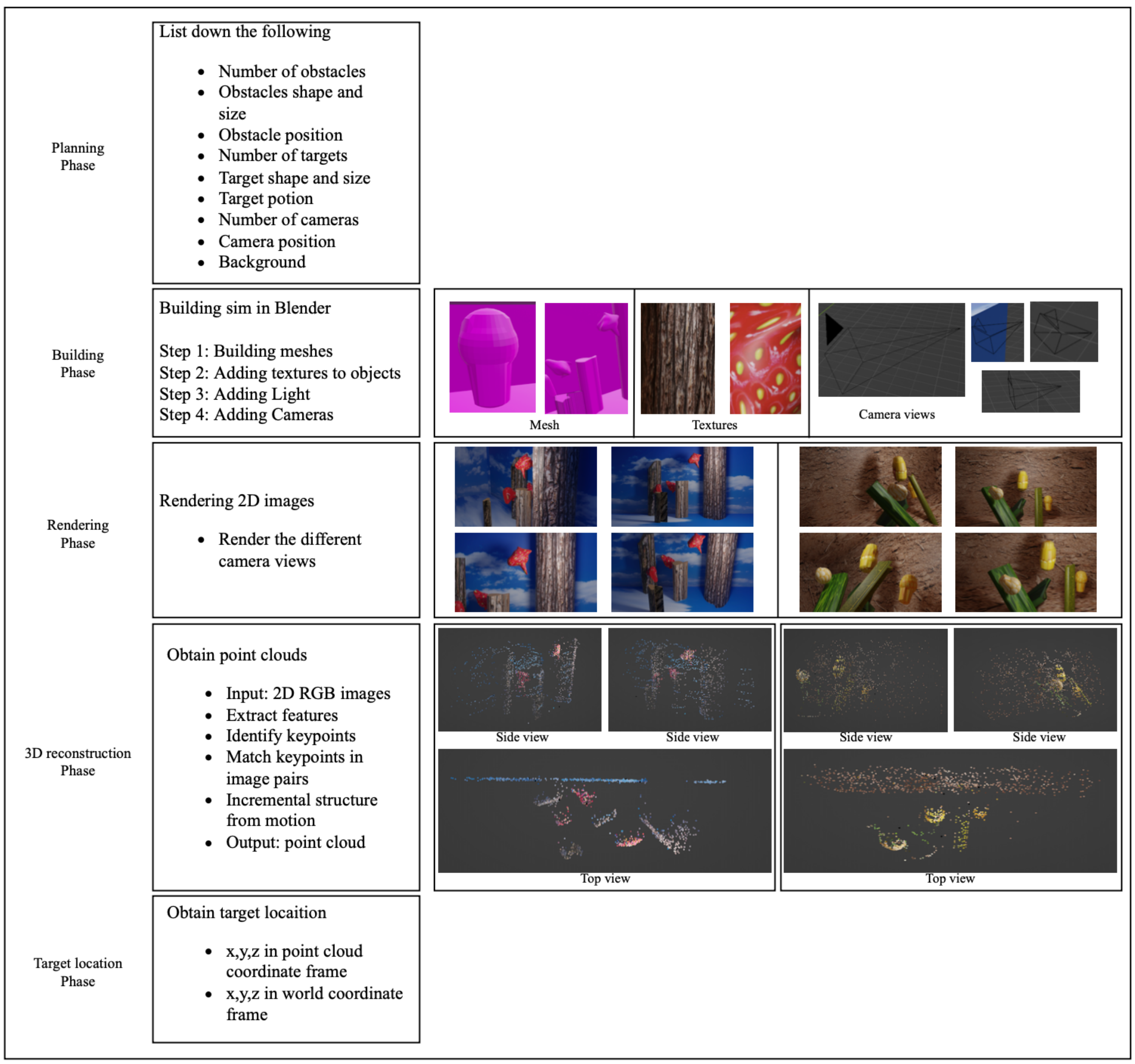
symmetry, and no variation in the shapes of the objects. Each mesh was molded in unique ways with unique textures. Protrusions were added to objects, and their shapes were made less uniform to mimic real-life settings. These modified environments resulted in dense 3D point clouds representing the simulation environments.

The 3D point clouds obtained were then used to get the targets' x,y, and z coordinates in the point cloud coordinate frame, PC. To get x,y, and z coordinates of points in real-world coordinate frame WC, we can apply a simple transformation:

$$T: R^{PC} -> \ R^{WC} \ defined\ by\ T(x) \ = A(x)$$

$$T = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix}$$

The obtained target locations can then be reached using various path planning methods. While this work was limited to creating realistic simulation environments and obtaining target locations from 3D point clouds, in future work, we would like to validate a path planning algorithm on SCA to reach a target in field settings.



References:

Rus, Daniela, and Michael T. Tolley. "Design, fabrication and control of soft robots." *Nature* 521, no. 7553 (2015): 467-475.

Kamtikar, Shivani, Samhita Marri, Benjamin Walt, Naveen Kumar Uppalapati, Girish Krishnan, and Girish Chowdhary. "Visual Servoing for Pose Control of Soft Continuum Arm in a Structured Environment." IEEE Robotics and Automation Letters 7, no. 2 (2022): 5504-5511

Sarlin, Paul-Edouard, Cesar Cadena, Roland Siegwart, and Marcin Dymczyk. "From coarse to fine: Robust hierarchical localization at large scale." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 12716-12725. 2019.

Sarlin, Paul-Edouard, Daniel DeTone, Tomasz Malisiewicz, and Andrew Rabinovich. "Superglue: Learning feature matching with graph neural networks." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 4938-4947. 2020.

Cartucho, João, Samyakh Tukra, Yunpeng Li, Daniel S. Elson, and Stamatia Giannarou. "VisionBlender: a tool to efficiently generate computer vision datasets for robotic surgery." Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization 9, no. 4 (2021): 331-338.

Zdziebko, Paweł, and Krzysztof Holak. "Synthetic Image Generation Using the Finite Element Method and Blender Graphics Program for Modeling of Vision-Based Measurement Systems." Sensors 21, no. 18 (2021): 6046.